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The Profitability of Contrarian Strategies and the Overreaction Hypothesis: Empirical Evidence

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Abstract

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The present thesis, motivated by controversies in the literature investigates a series of empirical issues relating to return predictability and Market Efficiency. More specifically, it seeks answers to the following questions: are returns predictable, and is this predictability universal or related to specific market types? Is this predictability genuine, or is it due to risk mismeasurement, microstructure biases, and market anomalies? How does the debate of single versus multi-factor models fit in this context? The focal point is the emerging market of Greece for the period 1990-2000. However, tests are also performed for the well-developed UK market for the period 1985-2000, in order to detect major differences in behaviour between the two market types.

The main results emerging from the empirical analysis indicate that asset returns are individually negatively serially correlated and predictable in both the short and long-term. Negative correlation can lead to statistically significant contrarian profits, the magnitude of which is reduced however when changes in risk, bid-ask biases, and thin trading, are considered. The January and the size effect do not explain results in Greece, however in the UK returns are predictable only for very small or very large stocks. Multifactor models describe asset returns better than single-factor ones for both markets. Results contribute to financial theory and to practitioners, and offer insight in contrarian strategies and a thorough understanding of return predictability patterns and risk.

The material contained in this thesis has not been previously submitted for a degree in this or any University.

Dedicated to my parents,
Christos and Irene

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3. *Multinational Finance Society* Conference, Paphos, Cyprus, June 30 - July 3, 2002.

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CHAPTER I.

INTRODUCTION

Contemporary empirical work in finance is aimed at understanding financial markets, describing their behaviour, and devising profitable trading strategies. There exist a paradigm in the literature as regards market behaviour, namely the Efficient Market Hypothesis (EMH henceforth). According to the EMH, asset prices reflect all available information quickly and accurately; stock returns follow a random walk[1] and thus markets are unpredictable. Put simply, long-term profitable trading strategies cannot be created (unless they carry an excess amount of risk) and no one can consistently outperform the market; it is thus pointless to spend any resources on the analysis and trading of assets. The rationale behind the EMH is that investors are greedy profit maximizers using every piece of information as soon as it becomes available to gain advantage over others; however, by doing so, they instantaneously incorporate information to prices and eliminate any arbitrage opportunities and chances for profits.

If the above statement of the EMH holds, there would be no room for risk adjusted profitable trading strategies able to consistently outperform the market. Nevertheless, although the empirical evidence for the EMH was overwhelming during the 60es and 70es, the situation changed after that, when evidence for return predictability emerged. Nowadays, there is still no consensus as to whether markets are efficient or not and the debate is ongoing, with empirical

[1] Random walk theory was formed for games of chance around the early 16th century (Hald 1990). It was first practically applied to financial markets by Samuelson (1965); and Fama (1970) based on Samuelson suggestions of stock movements unpredictability stated the EMH as we know it today in its three forms (weak, semi strong, strong). According to the Random walk theory, the best guess for the contemporaneous period's returns (R_t) of an asset, is what happened to it in the previous period (R_{t-1}) plus or minus an independently identically distributed error term (ε_t): $R_t = R_{t-1} + \varepsilon_t$, $\varepsilon_t \sim IID(0,\sigma^2)$. It can be shown using basic mathematical manipulation that: $R_t = R_{t-1} + \varepsilon_t \Leftrightarrow R_t - R_{t-1} = \varepsilon_t \Leftrightarrow \Delta R_t = \varepsilon_t$, but $\varepsilon_t \sim IID(0,\sigma^2)$, thus $\mathrm{E}(\Delta R_t) = 0$, and we thus understand that stock movements are unpredictable.

work clustered into two main strands, one that supports efficient markets and one that is against it.

In order for the reader to identify the controversies in empirical evidence, the focal points of the aforementioned debate of the two literature strands are briefly presented here. According to the first strand in the literature, markets are unpredictable, and the false impression of predictability is due to not taking into account for risk or changes in risk (Chan 1988, Ball and Kothari 1989). However, the other strand in the literature offers evidence that challenge the above suggestion (De Bondt and Thaler 1897, Lakonishok et al. 1994, Richards 1997), and as Dissanaike (1997) shows, using both Chan's (1988), and Ball and Kothari's (1989) methodologies -mentioned above- to deal with risk miss measurement, risk does not explain predictability. Another suggestion put forward by efficient market advocates is that microstructure biases are also responsible for the false impression of return predictability. For example, the bid-ask bias can give the false impression of negative serial correlation (Roll 1984, Jegadeesh 1990), while thin trading can give the false impression of return predictability due to positive serial correlation (Scholes and Williams 1977, Kaul Conrad and Gultekin 1997). Nevertheless, Jegadeesh and Titman (1995), Loughran and Ritter (1996) and others disagree with the above suggestions and provide evidence that predictability is still present and delivers profits after taking into account for microstructure biases, and suggest that there are other forces at work that are in most cases inconsistent with market efficiency. For example, the overreaction (De Bondt and Thaler 1985,1987, Pettengill and Bradford 1990, Balvers Wu and Gilliland 1999 etc) or underreaction anomalies (Klein 1990, Thaler and Womack 1995, Jegadeesh and Titman 1990 etc) could be responsible for return predictability. Some studies support that the well documented size effect proposed by Banz (1981), or the January effect as proposed by Rozeff and Kinney (1976), are responsible for the findings. It is most interesting that some studies offer evidence of a combination of over- or under reaction with the size effect (Claire and Thomas 1995), the January effect (Zarowin 1990), or the low priced firm effect (Ball et al. 1995, Baytas and Cakici 1999).

As can clearly be seen, there is a puzzle in the literature due to the contradicting evidence that enhances the debate and the uncertainty regarding the efficiency issue. Apart for controversies, the literature suffers from gaps as well. For example although a plethora of evidence exists for the US market, this is not the case for other developed and developing markets, and in addition, there are few comparative studies between the two sets of markets in some areas of predictability. Furthermore, most of the studies deal with one or two, each time, of the explanations for return predictability proposed earlier, and not with all simultaneously. Most importantly, no study in the predictability area due to overreaction has proposed a methodology to deal with the effect of continuous time variation in risk in order to rationalize contrarian profits. In addition, most studies have focused on either short or long-term contrarian strategies, and do not cover the entire time-horizon spectrum.

This thesis aims to identify the extent to which the major explanations put forward for return predictability hold, and to cover some of the aforementioned gaps in the literature. It seeks to find whether financial assets' returns are predictable or not, and in the process it asks:

- To what extent is risk or changes in risk responsible for any predictability?
- Can microstructure biases explain predictability?
- Alternatively, is it due to size and/or seasonality?
- Could overreaction or underreaction explain predictability?
- Is the predictability universal or specific to developed or developing markets, and to what terms do these two differ in their behaviour?
- Does the specification of abnormal returns, the investment horizons, the use of specific asset pricing models affect results?
- Can the predictability lead to significant profits?

In the quest for answers on the above questions, the thesis focuses more on the overreaction hypothesis, which states that investors, overreact to unexpected news driving prices out of equilibrium temporarily and later correct this overshooting as more information arrives in the market. The initial overreaction and later correction causes negative serial correlation and thus predictability, and an investor that has knowledge of this, can buy past losers and short past winners expecting them to become the opposite (due to negative correlation) and make a profit (this is called a contrarian strategy). More specifically, the thesis starts by analysing the developing Greek market for which no prior evidence exists relevant to the overreaction hypotheses. Based on De Bondt and Thaler (1985), it looks into overreaction and contrarian investment strategies and their ability to predict the future using several different long-term investment horizons to determine whether they affect findings. In addition it seeks to find whether the specification of abnormal returns influences findings, by employing different return specifications, namely: excess returns, market adjusted returns, CAPM adjusted returns, and time varying adjusted returns. It also tests whether predictability is due to seasonal effects, or volatility induced.

However, long-term contrarian strategies are one piece of the puzzle, since practitioners and academics are also interested in shorter-term strategies. Thus, as a next step, having established the length of predictability for long-run strategies that are up to six years, the thesis turns to short-term (weekly) investment horizons, building on a different methodology based on Jegadeesh and Titman (1995) for the same market. The first tests are related to the presence of short-term contrarian profits, and then under the need to define specific factors responsible for contrarian predictability, the thesis considers both overreaction and delayed reactions to firm specific news and market wide factors, as possible explanations. This is a key issue for the determination of profitable strategies as will be explained later. During the above process, the thesis also enquires about the sensitivity of the findings to the number of factors and the factors per se employed in asset-pricing models (using equally weighted and value weighted indices). Microstructure biases and seasonality are next on the agenda, and their effect is tested by employing several methods.

Interest then is directed to the well-developed UK capital market in search of similar patterns of predictability as for the emerging Greek market analysed.

The central points of attention are only short-term strategies, since longer-term ones have been tested for the UK by others (Clare and Thomas 1995, Dissanaike 1997 etc), but short-term contrarian strategies and the factors driving their profits have never been tested before. Profits and their decomposition are based on the methodology used for the Greek market for comparability of results, and size-sorted subsamples are employed to test whether results are restricted to a specific firm size. All the other issues examined for Greece (as described in the previous paragraph) are also analysed here. However, bid-to-bid prices are also employed for the UK in order to deal with the bid ask bias.

The thesis contributes to literature in several ways; the main contributions could be presented as follows:

- It provides evidence for overreaction related profitability for the Greek market for the first time, and compares it to the well-developed UK market.

- It provides short-term UK evidence for contrarian profitability and decomposes such profits to their sources for the first time.

- It improves overreaction tests by introducing the Kalman filter (well known in other areas of finance), and showing that most of the long-term predictability is actually owed to continuous changes in risk, which however can not be captured by other methods adopted in the past (e.g. Chan's 1988 method).

- It illustrates that the single-factor models could affect the results of predictability studies, and proposes the adoption of a multifactor model, with higher explanatory power, removing biases.

- It improves on the Jegadeesh and Titman (1995) methodology by considering annually rebalanced portfolios, and a sample of stocks that are continuously updated for new firms. The first avoids the problems created by considering size and risk to be constant, because as will be shown they change. The second avoids the bias introduced by sorting once and for all the stocks that are available at the beginning of the period, ignoring newcomers.

In the next chapter, the review of the literature is presented in order to unveil all relevant aspects of the empirical work, and the puzzle discussed in the introduction. The literature review also provides insight to the reasons for selecting the specific methodologies that the thesis employs, and will allow the reader to identify and better understand gaps and inconsistencies in the area.

The remainder of this thesis is organised as follows: chapter II reviews the literature, while chapter III discusses the Greek Market that is one of the focal points of the thesis. Chapter IV provides long-term predictability evidence for Greece, while chapter V provides short-term evidence for the same data, and chapter VI gives short-term contrarian evidence for the UK and comparisons with Greece. Chapter VII concludes the thesis, while the Bibliography and References form the last part of the thesis.

CHAPTER II.

REVIEW OF THE LITERATURE

2.1 Introduction

The chapter aims to examine the puzzle in the literature portrayed in the introduction. More specifically, it discusses return predictability and several related explanations. As mentioned in the introduction, predictability is related to the turbulent discussion of market efficiency, which goes back to Bachelier (1900). More recently, Samuelson (1965) set the new era in the discussion introducing randomness in share price fluctuation, and Fama (1971, 1991) based on Samuelson's suggestions stated the EMH. According to the EMH, markets are considered to be efficient when prices reflect relevant information quickly, fully, and accurately. There are three forms of efficiency:

Weak form: under which no investor can make abnormal returns based on past price information, because all such information is incorporated in prices.

Semi strong form: under which no investor can earn abnormal returns using publicly available information such as published accounting statements, earnings and other announcements, newspapers etc.

Strong form: according to which investors can not make abnormal returns even if they have private (i.e. non-public) information.

There have been other more recent statements of market efficiency that are more realistic; for example, prices reflect all available information up to the point that the marginal cost of obtaining that information doest no exceed the marginal gain from doing so (Elton and Gruber 1995). In general, the EMH simply states that any returns that can be made from holding a financial asset are not abnormal in any way, but just compensation for bearing systematic risk; prices, which are fair, follow a random walk, and no matter if they increase or decrease today, tomorrow's price has an equal chance of increasing or decreasing. Any departures from this reality are temporary, and no one can make abnormal profits on the long run, except by luck. The weak form market efficiency is connected with most overreaction and underreaction studies (return predictability), and the semi strong form event studies are connected with underreaction in most cases (price adjustment to information with a drift). One of the problems connected with these studies is the joint hypothesis problem, since most of them use an equilibrium model to determine expected returns and the rejection of efficiency might be due to using the wrong equilibrium model, and not the market per se.

Fama (1991) offers a brief review of the scientific dialogue relevant to market efficiency up to that point in time. He first looks into the predictive ability of past returns and illustrates that although early evidence on short horizon returns (e.g. Fama 1965, Fisher 1966) confirm the existence of autocorrelation in returns, they are statistically insignificant most times and explain only a small percentage of returns. Recent research (e.g. Lo and MacKinlay 1988) produces stronger evidence of positive auto-correlation and high abnormal returns, mostly for small firms, which however are reduced once microstructure effects are considered. Although shorter-term evidence suggests positive serial correlation in returns, evidence on longer-run strategies (three to ten years) reveal strong negative autocorrelation. Fama and French (1988) argue however that most of the above findings are confined to the 1926-1940 period.

Looking into other sources of past information, he reveals that earlier studies related to inflation and interest rates (Bodie 1976, Nelson 1976, Jaffe and Mandelker 1976, Fama 1981) indicate that the explained return variability is limited to 3% per annum; more recent work however by Rozef (1984), Campbell and Shiller (1988) etc, shows stronger results for longer periods. Past information can also be related to other forecasting variables such as dividend yields, E/P (Earnings to Price) ratios and B/M (Book to Market) ratios. Fama and French (1988) show that predictability based on dividend yield and E/P ratios is not constrained to the pre-1940 period like return based predictability. Fama concludes that such ratios seem more promising than past returns, since they might explain only 5% of monthly return variance, but they explain up to around 30% of longer (up to 60 months) run return variance.

As discussed in the introduction of the thesis, until recently markets were considered as efficient, and any work against market efficiency faced strong criticism; nonetheless, evidence that arrived in the early eighties showed that the opposite might hold. For example, the size effect (Banz 1981), seasonal effects like the January effect (Rozeff and Kinney 1976) and the inability to explain most of the stock return variability using the efficient market theory, are some of the problems that the EMH advocates faced. An even greater challenge to market efficiency stems from the literature of contrarian strategies, according to which, investors can make abnormal returns based only on past information. This is against the weakest form of efficiency, which states that no one should be able to make abnormal returns based on such information. The historical process against the EMH is as follows: Literature first demonstrated the existence of return predictability in the form of return momentum or return reversals. Then in order to take advantage of return reversals (continuation), contrarian (momentum) strategies were constructed. Contrarians that are the thesis main focus, observe past performance and expecting reversals, they go against the current, buying losers (stocks that have not done well in the past in terms of returns or other factors) and selling winners (stocks that have done well in the past in terms of returns or other factors). If return reversals exist, then winners (losers) should become losers (winners) delivering abnormal returns.

The literature review is initiated by looking into studies that provide evidence for return reversals. Although such evidence directly implies overreaction, the reversals are not attributed to any specific reason. This is because the aim of these studies was to test for return predictability, and finding return reversals among other things, fulfils this aim and they don't pursue the issue any further.

2.2. General Evidence for Return Predictability

An early study performed for several markets relevant to stock-price mean reversion is that by Poterba & Summers (1988). They test for the US market between 1926 to 1985, using monthly returns of value and equal-weighted NYSE[2] indices, and they find positive autocorrelation in the indices for the first year and negative for longer periods, (consistent with an initial momentum before reversals occur). Furthermore, they find that infrequent trading is not responsible for results, and that testing for different sample periods (1871-1925,

[2] New York Stock Exchange.

1871-1985) the patterns are the same, although smaller in magnitude. Other countries are also considered so as to reduce the possibility of data mining and specific US market effects. Monthly data on Canada and UK since 1919 and 1939 respectively are analysed together with data on fifteen other countries[3]. The outcome for these markets is consistent with the US, suggesting negative (positive) serial correlation for longer (shorter) than a year periods (except for Finland, South Africa and Spain). Based on the De Bond & Thaler (1985) and Lehmann (1987) evidence on negative serial correlation for individual stocks, they concentrate on eighty-two large firms for the period 1926 to 1985 using monthly CRSP[4] data. They establish that 12% of results are explained by stationary factors, and when they use a model separating the effect of permanent and transitory factors, the transitory ones account for 43% to 99% of the effect. The authors finally suggest noise trading drives transitory components.

Jegadeesh (1990) however partly disagrees with Poterba & Summers above, testing for the predictability of stock returns using an OLS[5] procedure on monthly CRSP data for the period 1926 to 1987. He finds negative serial correlation in small lags, but contrary to De Bondt and Thaler (1985) and to Poterba & Summers (1988), he finds positive serial correlation in longer lags. He tests for the January effect, and although the pattern of returns is different in January, this does not explain results. He also finds a size effect only in the month of January, with the absolute values of the slope coefficients of smaller

[3] Austria, Belgium, Colombia, Germany, Finland, France, India, Japan, Netherlands, Norway, Philippines, S. Africa, Spain, Sweden and Switzerland. Data are collected from the international monetary fund. Most countries are studied for capital gains only and for the period 1957 to 1986. The US is restudied for the same period.

[4] Centre of Research for Security Prices.

[5] Ordinary Least Squares.

firms been larger compared to large firms. To determine whether the correlations can be translated to significant profits, he uses three strategies. The first strategy (S0) uses ten equally weighted portfolios ranked in descending order according to predicted returns for each month between 1934 and 1987. Returns for the first five portfolios are positive and negative for the rest, with a difference of 34.33% per annum. The absolute values of abnormal returns are higher on January[6]. The second strategy (S1) and third strategy (S12) use a month's lag and a twelve-month lag respectively to rank stocks, and tests are carried out as before. Abnormal returns are estimated using the market model and the CRSP equal-weighted index as a proxy for the market. Differences between the extreme portfolios are 1.99% per month for S1 and 0.93% for S12, compared to 2.20% for strategy S0. Considering 0.5% two-way transaction[7] costs, strategies S0 and S1 deliver economically significant annual abnormal returns of 20.8% and 13.9% respectively, while the third strategy has no considerable profits. Controlling for size and changes in risk, taking in to account for the bid-ask spread & thin trading; do not explain abnormal returns.

A couple of years later in 1992, Brock, Lakonishok, and Le Baron utilize CRSP data to test two simple and heavily used trading rules on the Dow Jones Index between 1897 and 1986. The two rules tested are: (a) the moving average-oscillator and (b) the trading-range break[8], and results support technical

[6] The difference in abnormal returns of the extreme portfolios is 2.20% per month excluding January. In the month of January, the difference is 4.37% per month, which is quite higher.
[7] Since 91% of stocks included in portfolios are revised every month.
[8] The first rule refers to buying (selling) when a short-period moving average -equal to one or two days- rises above (falls bellow) a long-period moving average, equal usually to 200 days. Of course there are more complicated forms of this strategy. According to the second rule, buying (selling) should take place when the price of an asset penetrates the resistance level (support level), which is a local maximum (which is a local minimum).

analysis, thus returns can be predicted by past returns and the efficient market hypothesis is questioned. In addition, while testing for alternative explanations they find that stock returns are not fully explained by common risk measures (e.g. beta values). These results are also consistent with the overreaction hypothesis and contrarian theory.

Some might argue that results might be specific to the CRSP database, but unlike the studies mentioned so far, Chan, Jegadeesh, and Lakonishok (1995) do not use only CRSP data, interested in searching whether data selection biases are behind the abnormal returns of value versus glamour strategies. More specifically, they search whether CRSP and COMPUSTAT data matching is the cause of problems, since these two are not meant to be used together[9]. Building on the work of La Porta (1994) and Davis (1994)[10], they find that selection biases proposed by Kothari, Shanken, and Sloan (1995), are very small to explain results, and mostly concentrated in smaller firms. The authors use data on AMEX[11] and NYSE larger 20% of firms for the period 1963 to 1991, to test for the relationship between returns and B/M[12] ratio for included and excluded firms. They create equal-weighted portfolios based on B/M ratios starting on June and rebalancing them every year, and find that value stocks outperform glamour stocks by 5% annually for the next five years (which becomes 42.6% when compounded). Repeating the tests for firms with no COMPUSTAT data, the annual figure rises to 10% from 5%. Combining both data sets, the evidence

[9] The authors propose that selection bias can occur from each source's different handling of mergers, trade ceasing, differences in covered periods, COMPUSTAT back-filling data etc.
[10] The first study shows that higher returns persist even after accounting for selection bias in COMPUSTAT, and the second shows that the accounting ratios work for other data and before the COMPUSTAT files.
[11] American Stock Exchange.

is against sample selection biases; furthermore, CRSP and COMPUSTAT same period returns differ very little. Finally, using data for 1968 to 1992 they find that the reported missing data of CRSP firms on COMPUSTAT are not as large as 27% reported by Kothari, Shanken, and Sloan (1995), but is around 9.0%. In total, the selection bias problem seems to be very small and related to small firms; furthermore no evidence against overreaction or underreaction is found, and thus market efficiency is still questioned.

As already mentioned in the thesis, the above studies search for return predictability in general; the results they find however, are predominantly consistent with the overreaction hypothesis and contrarian strategies, while some evidence in consistent with delayed reaction and momentum strategies. In the sections that follow, the thesis thoroughly examines all the aspects of the most important studies involved in the scientific discussion of return predictability, beginning with the overreaction hypothesis, which is the focal point of the empirical research in this dissertation. In a next step, attention will be diverted to the underreaction hypothesis, and other possible explanations discussed in the introduction and put forward by literature as an explanation for return predictability.

[12] Book-to-Market value ratio.

2.3. Evidence supporting the Overreaction Hypothesis

2.3.1. Overreaction evidence for the US market

Faced with evidence against the EMH similar to the ones presented in the previous section, and in an effort to provide an explanation for this, scientists propose two major explanations: investor overreaction and underreaction. As regards overreaction, the focal point of this subsection, investors tend to be overly optimistic (pessimistic) about stocks that have performed well (badly) in the past, and drive prices away from equilibrium temporarily until new information is available and the over-pricing or under-pricing becomes obvious, and thus prices revert towards their fundamental values.

De Bondt and Thaler's (1985) paper in the Journal of Finance is taken to be the starting point of the overreaction hypothesis, not only because the paper formally states the hypothesis, but also because the methodology suggested has been applied, and is still applied by numerous studies. The paper investigates the overreaction hypothesis and its significance for NYSE monthly data between January 1926 and December 1982. The study tests two main hypotheses: (a) extreme stock price movements in one direction will be followed by movements in the opposite direction, and (b) the more extreme the price movements the greater will be the subsequent adjustments.

De Bondt and Thaler report that three years post-portfolio formation losers outperform the market by 19.6% on average, and winners under perform the market by 5.0%[13], while the difference between the ACAR's (average cumulative abnormal returns) of Losers and Winners is positive (24.6%). The overreaction effect is observed mostly during the second and third year after portfolio formation, and at the same time, the larger the previous periods loses or gains are, the larger the reversals in the subsequent period are. Furthermore, there seems to be a January effect, since most of the excess returns are realised in Januarys (8.1%, 5.6%, and 4.0% for the first, second and third January subsequent to portfolio formation respectively). However, controlling for it, they suggest that the overreaction effect is other than the January effect. A very interesting finding, which however was later attacked by Zarowin (1990), is that loser portfolios not only outperform winners, but they are also less risky since the past loser beta is 1.026 while the past winner beta is 1.369 on average.

Although the study is very important, showing the pathway for future scientific discussion, it left many unexplained results, such as abnormal January returns. In addition, Chan (1988) and others challenge the study for not capturing the effect of systematic risk changes. However, Chan's methodology (that will be discussed in detail) is also challenged by others (see for example Dissanaike 1997). The author of this thesis believes however, that risk does change over time as Chan suggested, but his methodology is unable to capture that, and perhaps a method that could take into account for continuous time-variation in risk would be more capable of doing so. It is thus evident that there is a gap in the literature, which has provided part of the motivation for the thesis first empirical chapter.

[13] Overreaction effects are found to be asymmetric: larger for previous losers and smaller for previous winners.

Pettengill & Jordan (1990) put the above paper to the test, using 1962 to 1986 NYSE & AMEX daily data and three-year overlapping samples and equally weighted excess returns portfolios. Contrary to De Bondt and Thaler, they find an asymmetric reaction: extreme losers become winners (21.5% abnormal profits), but extreme winners remaining so (4.68% abnormal profits) although they gain less than earlier. This can be risk related: higher (lower) testing period returns of past losers (winners) can be due to an increase (decrease) in risk compared to the formation period, which could be a result of size changes according to Chan (1988). Asymmetric reversals may also be consistent with Brown and Harlow (1988) who suggested an asymmetric reaction to bad and good news. It could also be due to the fact that contrarian profits may not be related to negative autocorrelation but to positive cross-serial correlations between stocks, i.e. a lead lag effect (Lo and Mackinley 1990). For example when there are only two stocks in the market (A & B) with the stock A leading stock B, a price increase for A would indicate a price increase for B in the near future. A contrarian could benefit (although for the wrong reasons, since there does not have to be any negative autocorrelation) from this relationship, because he would sell stock A that has done better, to long stock B. This could explain why losers become winners, but not the opposite. Pettengill & Jordan also find that smaller firms exhibit higher abnormal returns, consistent with the size effect literature claims that market value is a good proxy for risk, with smaller firms being riskier. In line with De Bondt & Thaler, they find that higher loses during one period imply more profits in the next one, and that two-thirds of abnormal returns for losers[14] occur in January[15].

[14] Who are still losers however, for the first six months of the testing periods.

Chopra, Lakonishok & Ritter (1992) use the Ibbotson (1975) RATS procedure on monthly CRSP NYSE data for 1926 to 1986, and find that past losers outperform winners by 14% per annum[16], and by 70% for the whole testing period. However, when using the Sharpe-Linter CAPM[17], only 2.5% of the above abnormal performance is explained by overreaction, while using post-raking returns and betas this goes up to 6.5%. Consistent with the size effect literature they find that size explains a portion of results. This could be expected as share prices are highly correlated to size (Bowman and Iverson 1998). Also, smaller firms are normally more risky, less liquid, and are followed by a smaller number of analysts (Lakonishok and Vermaelen 1990), as can be seen throughout the thesis and especially in sections 2.7.2.1 & 2.7.2.2. The authors however state as another reason for the findings that small firms overreact because they are held by individuals who overreact, while institutions that do not overreact hold most large firms. They also find in line with De Bondt & Thaler (1985) no overreaction for the first holding year out of January.

Although all the evidence presented so far rely only on information publicly available, the next two papers focus on insider trading to test for overreaction. Seyhun (1990) for example, uses the 1987 crash to test for price reversals and whether fundamental value shifts in an efficient market context could be behind them[18] (Black 1988, Roll 1989). Insider trading data are obtained from SEC[19],

[15] Most of the previous losers January abnormal return is concentrated in the last trading day of December and January's first four trading days.
[16] Past losers have 24.3% of excess returns and winners have an annual average of 10.3%.
[17] Capital Asset Pricing Model.
[18] His reasoning is as follows: if the price performance is due to a shift of fundamental values, then shifts in expected returns or systematic risk should predict the price movements during and after the crash, and insiders trading should not be connected with the behaviour of prices. On the other hand if overreaction is important, then the opposite should hold, with insiders been net-purchasers of their stocks, purchasing more stocks the more the false under-valuation is.

while NYSE, ASE[20] and NASDAQ data around the crash (1987 and 1988) are collected from the CRSP. Results significant at the 1% level show that insider net purchases and net share purchases increase during the crash and after that, while sales do not (the increases for top executives are even higher). The observed behaviour is consistent with overreaction: insiders do not expect the crash (because they are not selling before it), and start buying during the crash, recognising low prices compared to fundamental values (caused by outsiders' overreaction). As regards the suggestion that price declines are due to a decline in risk aversion, the answer he provides is that then, insiders should have been selling and not buying in an effort to reduce their wealth invested in the falling stocks. The author concludes that after searching for the explanatory power of risk and insider trading, only the second is found to have power. Stocks that move further away from their fundamental values are the ones that experience higher future recovery, and higher insider trading[21], consistent with overreaction. The thesis suggests that another explanation for results could be that the true fundamental values at work are not considered. In addition, it seems that the assumption that all insider trading is captured by the sample, and that insiders don't overreact and price assets correctly, are both very strong.

Another paper on the same subject is that by Rozeff and Zaman (1998). Their difference from the paper above is that they employ accounting ratios based on Lakonishok, Shleifer and Vishny (1994) who suggested that such ratios measure the length of price deviation from fundamental values due to overreaction. The

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This is logical, since insiders are supposed to know the fundamental values of their stocks, and should try to arbitrage away the profit.

[19] Securities and Exchange Commission.

[20] American Stock Exchange.

paper also looks into alternative theories: the diversification[22] and the holding hypothesis[23]. The intuition is that value (growth) stocks are undervalued (overvalued); insiders with superior knowledge take advantage of this, buying value stocks and selling overvalued stocks. If this is the case, then there is a relationship between these stocks and insider trading (Seyhun 1986, and Rozeff & Zaman 1988). They find that as one moves from glamour to value stocks, insider-buying activity increases significantly, and that as past returns increase, insiders buying activity decreases. However, contrary to the previous studies, past returns do not explain results, and insider-buying increases based only on the accounting ratios. Nonetheless, the paper rejects the random walk hypothesis, while fully supporting the overreaction hypothesis. Extending the return period to 36 months and repeating tests does not alter the outcome.

On an earlier study related to the overreaction hypothesis, French & Roll (1986) test for the cause of high volatility during trading hours compared to lower volatility during non-trading hours. They propose three possible explanations, of which the third one is that noise trading drives results, possibly because investors overreact initially affected by other traders' selections, and slowly correct in the future, leading to smaller variances for longer periods than the ones observed for daily intervals. This goes back to the theory of Keynes and

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[21] This is by far the most significant explanatory variable for post-crash return behaviour.

[22] The diversification hypothesis says that: due to resent price increases in stocks, there are CF/P ratio decreases, since the denominator increases. Insiders sell this type of stocks just because they find their portfolio to be concentrated on them, and in no connection with price diversions from fundamental values. Nonetheless, although not considered here, portfolio revision and returns might be affected by long-term liquidity. For example according to Amihud (2002) expected (unexpected) illiquidity positively (negatively) effects returns, especially of smaller firms, explaining time series variations of premiums for such stocks (see also Chordia et al., 2000, and section 2.7.1.5 for shorter term illiquidity and its effect on contrarian portfolios).

"animal spirits" or "higher order beliefs", where economic problems are modelled as a game of incomplete information, and investor payoff depends not only on his actions, but also on the actions of others and economic fundamentals (see for an example Morris et al., 1995). These actions are related to animal spirits and taken under such a state; in "general theory", Keynes argues that: "a large proportion of our positive activities depend on spontaneous optimism rather than mathematical expectations...our decisions to do something...can only be taken as the result of animal spirits - a spontaneous urge to action rather than inaction- and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities." (p. 161-162). The interpretation of the above statement varies, and one version could also be that animal spirits are related to irrationality of economic behaviour, which can be related to excess optimism and pessimism, and thus miss pricing due to overreaction. It is in this spirit that Philippatos and Guth (1989) discuss how intelligent markets can be big enough for traditional economics as well as evolutionary and behavioural approaches, trying to establish a more representative model. Also, Tirole (1982) integrates rational expectations equilibrium in to a dynamic speculation model, and finds that investors trade on a combination of market prices and personal information

French & Roll collect CRSP daily data on all NYSE and AMEX stocks for the period 1963 to 1982. They form and test three hypotheses: (a) high trading time volatility is due to public information observed in normal business hours, (b) high trading time volatility is due to private information observed when stock

[23] The holding hypothesis suggests that executives in successful firms (which have low CF/P

markets trade, and (c) high trading time volatility is due to pricing errors (overreaction) when stock markets trade. They find positive first-order and negative higher order serial correlation, consistent with the overreaction hypothesis. They then separate returns in to three components: a rational information component, a miss pricing component, and a bid ask error, and find that overreaction (miss pricing) affects only trading days by 4% to 12%. Most of the volatility differences between trading and non-trading hours are not explained by overreaction, but can be attributed to information-flow differences. A very important aspect of the paper is that it acknowledges for the first time the possibility of a combined effect of underreaction and overreaction, suggesting initial overreaction for daily-weekly returns and the possibility of underreaction when corrections are done.

The results of this subsection are clearly in favour of the overreaction hypothesis, and the ability of contrarian strategies to profit from the predictability induced by the negative serial correlation related to the overreaction hypothesis. However, the main or only focus of the above studies is the US market using CRSP data most times. There is thus room for doubt as to whether the overreaction hypothesis is market specific, or holds for other markets as well, and to what extent? Could it be more significant for other developed markets or for smaller less developed markets given the possible higher information asymmetries in such markets? The next subsection will provide answers on the generality of the overreaction phenomenon.

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ratios) are paid a percentage of their salaries in stocks. They then sell them to convert them to

2.3.2. Evidence from other Markets

Da Costa and Newton (1994) test the overreaction hypothesis for the Brazilian stock market, using data for the period 1970 to 1989, and both market and CAPM adjusted returns. The results are positive for the overreaction hypothesis, with stock prices exhibiting higher price-reversals than the AMEX or NYSE. Using Chan's (1988) methodology to take into account for changes in risk, they demonstrate that risk -at least as expressed by CAPM betas- cannot explain returns. They also find evidence consistent with other studies showing the overreaction phenomenon to be asymmetric for losers and winners.

The same asymmetry (past losers experiencing larger absolute reversals than past winners) is instituted by Bowman & Iverson (1998) that perform a short-run overreaction study for situations following a sharp price-change on the New Zealand Stock Exchange. They use weekly data for the period 1967 to 1986, and get a positive outcome for the overreaction hypothesis, with 2.4% of abnormal returns in the week following a large price drop (losers make a profit becoming winners), and negative abnormal returns of 1.5% following a large price increase. Also the higher the previous loses or gains, the higher the future reversals seem to be. They then show that low-priced firms do not drive results, by dividing the sample to less than one US dollar and more than 1 US dollar firms, and showing that these two samples have no different behaviour compared to the overall sample. Risk and seasonal effects are also controlled for, but no differences are observed indicating that none of the two explains the

obtain cash for their every day needs, and that is how the observed pattern is created.

results. Using share price (which is highly correlated to size) they control for size by erasing observations until losers and winners are of equal price on average, but results are again not altered. Next, they propose that the bid-ask bias does not explain results, since stock prices are highly negatively correlated with the bid-ask spread, and even when using alternative ways to test for bid-ask bias, it does not have any explanatory power. Results are positive for the overreaction hypothesis. They are negative however, for the size, seasonal, risk, and bid-ask biases explanations.

Two years later Grinblatt & Keloharju (2000) search if past stock-return behaviour affects the willingness of agents to buy or sell stocks in Finland, and if the sophistication level of the agents has any influence, being closer to behavioural models. They collect data on the 16 largest stocks representing more than half of the total Finnish market capitalisation, from the Finnish Central Securities depository (FSCD) for the period December 1994 to December 1996. They find that foreign investors follow momentum strategies, while domestic investors -especially less sophisticated households- follow contrarian strategies. In other words the more sophisticated an agent the closer he is to momentum strategies, and the further away from contrarian strategies. The evidence also shows that foreign momentum traders outperform domestic contrarian ones, who still however have a positive return. We are however somewhat concerned with the length of the sample period and the small firm sample used, and suggest that the results of the study be treated with caution.

A more general study looking into a group of markets is that by Balvers, Wu, and Gilliland (1999), investigating 18 countries with developed capital markets[24] between 1969 and 1996 using annual data on country indices and a world index. The authors test whether stock returns are mean reverting, using a panel framework, the Seemingly Unrelated Regression technique (SUR), and performing Monte-Carlo simulations to find the critical values they should employ for their tests. Initially, they do not reject the hypothesis of no mean reversion, but panel tests show that mean reversion exists. To prove this, they run Monte-Carlo experiments; the power of their tests is found to be superior to the single-factor models' power, and almost perfect, so they attribute the initial results that were against mean reversion to lack of power, and they drop them. Furthermore, in comparison to past results by Kasa (1992), Cutler et al. (1991), their own seem to be stronger due to the panel-tests.

Bremer & Hiraki (1999) study the Tokyo Stock Exchange (TSE) in Japan, looking into short-run return reversal evidence and the connection of such reversals with lagged trading volume, using data from January 1981 to June 1998 on 1318 stocks. The study is interesting for one more reason, it does not suffer from the bid-ask bias, due to the trading system followed in the TSE, and thus one of the possible explanations put forward by EMH advocates for return reversals has no power here. The paper establishes that price reversals for the TSE are significant for both winners and losers (but larger for losers), and that results are not sensitive to the portfolio formation method although some changes could occur for losers when forming portfolios differently. High

[24] Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan,

volume winners are not different from low volume ones, while high volume losers experience larger reversals than low volume ones, but volume does not account for most of the results, and using different volume measures and horizons does not alter results significantly. They next create size ranked portfolios and observe that the smaller the firm the larger the reversals. Incorporating the volume information, further contributes to the effect, but does not explain results completely. They then control for the possibility of the Keiretsu system effecting results, dividing firms in to keiretsu (firm groupings with large cross share holdings) and non-keiretsu firms, but observe no difference in their performance.

Another study for the Tokyo Stock Exchange for the overreaction hypothesis is that by Gunaratne & Yonesawa (1997), the difference from the above study is that this one employs earlier data from 1955 up to 1990, and involves long-run tests instead of short-run ones, since portfolios are formed based on the past 48 months performance. The evidence provided, supports the overreaction hypothesis; more specifically past losers' risk adjusted abnormal returns are 11% above winners on the first year after portfolio formation. Controlling for the January effect, they find that it does not explain returns (consistent to De Bondt and Thaler 1987). Overall results are positive for the overreaction hypothesis and once again consistent with those for the US, although the two markets are very different in, market system, organisation, culture etc.

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the Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK and USA

Kang et al. (2002) use DATASTREAM weekly Chinese data for 1993 to 2000 on 268 "A" shares available only to local investors, with low trading volumes (evidence should be seen under this light). They use Jegadeesh and Titman's (1995) methodology for several short and longer-term strategies, and they find short-run evidence consistent with the overreaction hypothesis and medium term evidence consistent to the underreaction hypothesis. In addition, they consider size, changes in risk using Chan's (1988) methodology, and microstructure biases such as non-synchronous trading and the bid-ask bias (skipping a day/week between portfolio formation and holding), but they find no change after doing so. However contrary to the US results of Jegadeesh and Titman, they find the delayed reaction (that induces a lead-lag effect) does not contribute positively for contrarian strategies but to momentum strategies, nonetheless short-term reversals and profits from such reversals are present.

Alonso & Rubio (1990) test for the overreaction hypothesis in the Spanish market using long run horizons. They find strong price reversals and positive evidence for the overreaction hypothesis, and they also find that results are not explained by the size effect. Results indicate that a year after portfolio formation, past losers make 24.5% more than past winners.

This important subsection established the generality of the overreaction hypothesis, providing plethora of evidence that support it for different countries with different cultures in both Europe and Asia, and so overreaction is not market specific. Furthermore, overreaction holds for countries with all three different market systems like the US, Germany and Japan.

2.3.3. Overreaction evidence based on accounting ratios

There has been a lot of discussion regarding the ability of accounting ratios to predict future prices. An example of such ratios is the Earnings to Price (E/P) ratio (Basu 1977), Book to Market (B/M) ratio (Chan, Hamao, and Lakonishok 1991), Cashflow to Price (CF/P) ratio (Rosenberg, Reid, and Lastein 1985).

For an example regarding overreaction, a strategy of shorting glamour stocks and longing value stocks based on the above ratios can deliver abnormal returns. Dreman & Berry (1995) who examine contrarian strategies based on accounting ratios seem to agree with the above statement and suggest that abnormal returns are genuine and caused by overreaction, underreaction, or both in some cases. Three other explanations for the abnormal returns of value compared to glamour stocks have been considered though in literature, which are in line with the EMH. The first explanation is that returns are not abnormal at all, but just compensation for investors bearing excess risk (Fama and French 1993,1996). The second one is that results are due to data snooping (Black 1993), and the third explanation involves data selection biases (Kothari, Shanken, and Sloan 1995). Another (behavioural) explanation suggested by Daniel and Titman (1997) is that value characteristics are responsible for the value premium and not risk, e.g. investors prefer growth stocks and not value stocks, which results to low price, and high expected returns for value stocks.

De Bondt & Thaler (1990) search whether analysts who have skills, knowledge and information that private investors do not have, overreact. The basis of their study is once again Kahneman and Tversky (1973) who find people to overreact to recent news and underweight past news. De Bondt and Thaler use two strategies, one with an annual horizon and another with a two-year horizon between 1976 and 1984, and focus on Earnings per Share (EPS). They try to find whether systematic errors in EPS forecasts are linked with changes in forecasts, and especially if there exists a revision-reversion of previous extreme forecasts. In addition, they try to establish whether the forecast bias is negatively correlated with the amount of certainty for the future. They find that forecasts are extremely optimistic, and magnified in the two-year period, and that the larger the forecast error the larger the future reversal is. December reversal on April's one-year forecasts is 18% of the original predicted, and goes up to 38% for two-year forecasts. Thus, analysts overreact as private investors do, even after controlling for data entering errors and stale forecasts. Furthermore, trying to find what causes the initial excess optimism or pessimism of future earnings, they employ ratios. Although they find that high (low) MV/BV[25] and high earnings trend firms are positively correlated with excess optimism (pessimism) for stocks, they cannot explain a large enough portion of the effect to produce answers. The paper establishes overreaction for analysts, but does not find an answer for the causes of overreaction, and could have used a larger testing period so as to have more general results and not confined to the certain period and data. I believe that due to the stock inclusion criteria used, the sample is biased towards large and well-established firms, which however in my opinion is good, because it provides an answer to those that suggest the size effect as the cause of positive findings for overreaction.

[25] Market-to-book value.

With respect to other markets, Brouwer, Van Der Put & Veld (1997) focus on the UK, France, Germany, and Netherlands using large firm data for the period between June 1982 and June 1993. They test for value strategy profits[26], by constructing five annually rebalanced portfolios, using four ratios to classify stocks: E/P, CF/P, B/M, and Yld[27] and a regression model to test simultaneously for the significance of the value ratios. They find that consistent with the overreaction hypothesis, portfolios with high value ratios (losers) outperform low value ratio ones (winners). More precisely high E/P stocks outperform low ones by an average of 5%, while high CF/P stocks outperform low ones by 20.8%, high B/M stocks outperform low by 10%, and high Yld stocks outperform low ones by 5.2%. In addition, high E/P stocks do better than low ones 72% of times, while high CF/P do better at all times, and high B/M & high Yld stocks do better at 64% and 91% of times respectively. They next test for alternative explanations such as size and risk. More specifically, controlling for risk, they find that small firms tend to do better in the coming year, and that the only significant factors are CF/P and dividend yield. If it is higher risk that drives value stock returns, then in falling markets they should do worst than glamour ones, but they find that although value stocks' variance is higher, high CF/P stocks outperform low[28] ones even in falling markets. They conclude that a CF/P based contrarian strategy will outperform the buy and hold one. I believe however, that they fail to understand that risk changes over time, as riskier firms today might become less risky tomorrow, and that can explain the high CF/P abnormal returns. Another explanation could be that beta does not capture risk

[26] Using a value strategy involves buying stocks with low prices compared to their earnings, cash flows-to-book values, dividend yields and other measures.
[27] Yld: dividend yield.
[28] We are always speaking of differences in the extreme, that is the highest minus the lowest.

correctly and consequently is inefficient as a systematic risk measure. Furthermore, the sample period they use is very small and reduces the generality of their results. I further believe that the factors employed should have been orthogonilised because the correlation between the factors is very high (CF/P to E/P by 43%, to B/M by 39% etc). Finally, readers are not informed of the criteria under which each country's participation percentage is decided.

Up to this point, the literature review has presented a multitude of studies that provide positive evidence for contrarian strategies and the overreaction hypothesis, not only based on past returns but also on accounting ratios. Furthermore, this evidence is not related to a specific market or sample period, but a large number of markets with different cultures and systems, and for different periods. However, it will be shown in the next subsection, that not all evidence is supportive of the overreaction hypothesis. Conrad & Kaul (1993) for example find evidence proposing a low-priced firm effect as responsible for results instead of overreaction, and also suggest that using cumulative raw or abnormal returns instead of buy-and-hold returns is responsible for the false impressions of overreaction. Another example of negative evidence for the overreaction hypothesis is the study of Kaul & Nimalendran (1990) who suggest that it is the bid ask bias, and not overreaction that causes negative serial correlation in stock returns. These and some other recommendations that are against the overreaction hypothesis will be the core of the next subsection.

2.4. Evidence against the Overreaction hypothesis

Bernard & Thomas (1990) investigate whether earnings announcements effect stock prices in the short-run aiming to find if stocks fail to incorporate the current earnings' information context for future earnings. Employing NYSE & AMEX data for a thirteen-year period, the evidence shows predictability in the three days surrounding the announcement, and a positive declining relationship between the announcement quarter's earnings (t) and de-trended quarters (t-1, t-2, t-3), and a negative relationship with quarter t-4, not explained by seasonality. According to their findings, an investor can use past earnings information to make abnormal returns of 2.1% to 2.9% (depending on the regression used) over the three-day announcement interval; and if the investor knows earnings three days before the announcement, abnormal returns of double magnitude can be made (4.2% and 4.4%). This indicates that using historical data compared to using perfect prior earnings knowledge can lead to half the abnormal returns. Another interesting finding is related to the size effect, more specifically the smaller the firm's size the larger the abnormal returns, with small firms experiencing 3.4% abnormal returns, and medium and large firms experiencing 2.2% and 1.2% respectively. The study concludes however that any profits not owed to the size effect can still be attributed to investor underreaction but not overreaction.

Chen & Sauer (1997) use CRSP monthly data for the period between 1926 and 1992 to test for the overreaction hypothesis using twenty stock portfolios ranked on the basis of their previous five-year buy-and-hold returns, creating fifty-eight, four-year ranking periods. They discover that not only the loser portfolio outperforms the winner portfolio by 11% per annum for the 66 years tested, but there also seems to be an asymmetric effect[29] consistent with De Bondt and Thaler (1985) and other studies, with all t-statistics significant at the 1% level. Next, an arbitrage portfolio's returns (losers minus winners) are computed for each post-ranking period to test whether the effect is persistent over time, which however is not the case, with returns taking both positive and negative values in different times. Then in further search for differences in overreaction behaviour during different economic eras, they segment their sample in to four sub-periods: pre-war period, post-war, pre-energy-crises, and the post-energy-crises. The overreaction hypothesis holds for the first and third period[30], with significant results and with losers outperforming winners by 25% and 18% respectively. On the second and fourth period, results are contra the overreaction hypothesis and together with other periods results lead to the conclusion that overreaction is not consistent over time. Furthermore, they show that for all periods, the portfolio with the highest returns also has the highest standard deviation, and is not a consistent winner. Plotting monthly arbitrage returns with risk premiums gives a positive relationship between them. They finally propose that losers do better (worst) than winners in a market upturn (downturn), and perform identically in a level market. These explanations are consistent with the size effect[31], but the worst news for contrarian strategies is that after controlling for changes in risk, there is no positive evidence for overreaction.

[29] As has been mentioned already, according to this effect: the more the past loses are, the greater the gains in the future are.
[30] In the third period however, winners outperform losers in some cases!
[31] Since losers tend to be smaller firms.

Gaunt (2000), tests for overreaction using the De Bondt and Thaler methodology for data on Australian stocks during the period 1974 - 1997. He finds return reversals and thus predictability, which however is reduced once Chan's (1988) methodology is used to take into account for time-variation in risk. Furthermore, he finds that most of the past losers are smaller and thus perhaps more risky firms than past winners are. The most important finding with negative implications for contrarian strategies is that once buy-and-hold returns are used, any predictability and abnormal profits for contrarian strategies disappear. Given that other studies for the same market, Brailsford (1992) who uses data between 1958 and 1987, and more recently Allen and Prince (1995) find negative evidence for return reversals and contrarian strategies, results of this study must be approached with care, since they might either be market specific or due to the use of buy-and-hold returns. For example Fama (1998) criticises the use of buy-and-hold returns, providing another reason for approaching the preceding study with caution.

Fama's (1998) study is very important with many implications as shall be observed, and looks into market efficiency with respect to evidence for overreaction or underreaction of stock prices to certain events. On the theoretical side, Fama puts on the defence for the EMH proposing that the frequencies of both overreaction and underreaction are the same, and thus consistent with the efficient market hypothesis they both have an equally random chance of occurring. Furthermore, he believes that long-run anomalies are very sensitive to the different methods and models used to estimate expected returns, and most anomalies disappear when different approaches are used, and can be thought of as chance events. He further suggests that for a model to be considered as an alternative to the efficient market hypothesis (EMH), it must describe reality better than the EMH, and argues that this is not the case. Fama also suggests the bad model problem as an explanation, according to which, the models used can produce biased results, and as foretold in the thesis, the problem becomes even larger when buy-and-hold abnormal returns are used instead of averages of monthly abnormal returns (AARs) or CAR's, informally criticising the suggestions of Conrad & Kaul (1993) in favour of buy and hold returns. He also proposes the use value instead of equal-weighted portfolios.

On the empirical side, Fama shows that except for small firms whose returns are not well described by available models, anomalies cease to exist when tests are extended to other periods, or when using value-weighted portfolios instead of equally weighted ones, or when using a different model. He further shows that overreaction or underreaction based on events such as initial public offerings (IPO's), or seasoned equity offerings (SEO's), share buybacks, tender-offers, or dividend initiations, do not exist when the method for abnormal returns estimation is changed. Furthermore, overreaction based on merger events is shown to be economically insignificant, and the use of value-weighted portfolios eliminates or reduces substantially the anomaly confirming Fama's suggestion that it is a small firm problem. Fama states that the only results that are not explained by this study are the ones by Ball & Brown (1968) on post-announcement drift (underreaction), and Jegadeesh and Titman (1993) short-term underreaction. However, given the plethora of studies that are put to the test here, it is strange that De Bondt & Thaler's (1985) results are not tested.

Fama finally puts forward three other explanations for abnormal returns of value compared to glamour stocks that have been proposed in the previous subsection. The first suggestion is that the returns are not abnormal at all, but just risk compensation (Fama and French 1993,1996). The second one is that results are due to data snooping (Black 1993), and the third explanation given, involves data selection biases (Kothari, Shanken, and Sloan 1995).

How do other studies respond to the above declarations? Chan, Jegadeesh, and Lakonishok (1995) following the work of La Porta (1994), and Davis (1994)[32], have already shown that the second explanation of selection biases does not hold. Furthermore, other papers like De Bondt & Thaler (1987), Lakonishok, Shleifer & Vishny (1994), Anthony Richards (1997), that will also be discussed thoroughly, have shown that risk is not the explanation for profits. Gishan Dissanaike (1997) (discussed in the review section devoted to the size debate) also disproves, as shall be shown, some of the above explanations using UK data. Baytas & Cakici (1999) propose that part of the results can be explained by overreaction, while Kaul & Gultekin (1997) propose that bid ask biases explain only part of results and that overreaction explains a significant part in most cases. Tim Loughran & Jey Ritter (1996), covering the gap left by Fama on the De Bondt and Thaler (1985) results, find that although results can be explained by both overreaction and normal risk compensation (thus risk is not a complete explanation), they cannot be explained by bid-ask biases.

[32] The first study shows that higher returns persist even after accounting for selection bias in COMPUSTAT, and the second shows that the accounting ratios work for data other and before the COMPUSTAT files.

As can be seen, findings are conflicting, and based on the plethora of opposing explanations for predictability the literature review moves to the underreaction hypothesis, which is competitive to the overreaction hypothesis. According to it, investor reactions to new information are delayed leading to a longer period for asset prices to incorporate new information. This causes positive serial correlation and price momentum: positive (negative) price movements, followed by more positive (negative) price movements. As shall be seen later though, overreaction and underreaction are not mutually exclusive, but can both work together towards contrarian profits. The review, will first concentrate however on evidence only for underreaction, and it will be enriched with evidence supporting claims on the partnership of both hypotheses.

2.5. Evidence supporting the Underreaction Hypothesis

Ball & Brown (1968) use Standard & Poor's data on income announcements and CRSP monthly stock data for the period 1946 to 1966, employing two models, one for market expectations and another for market's reaction when expectations are proved false. They suggest that if actual income is less than expected this is bad news, and its release should lead to a negative correction around the release date, and that the opposite holds for good news. They use three portfolios: one with positive, one with negative forecast errors, and one with all firms, and find that when income forecast errors are positive (negative) abnormal returns are positive (negative), while the whole sample returns are slightly negative. The evidence suggests momentum due to underreaction, because a drift is observed[33], consistent with Michaely, Thaler and Womack (1995); the results however, are not easily generalised because the paper may be characterised by a survivorship bias.

Another early study that finds positive evidence for underreaction with respect to an accounting ratio, namely the price-to-earnings (P/E) ratio, is an early one by Basu (1977). The study shows that the NYSE is slow in incorporating publicly available information in stock prices, which is consistent with positive serial correlation and momentum. According to the findings, profits can be made by using past information based on accounting ratios, against the EMH.

In a paper of the same era, Guy (1978) finds evidence for market underreaction to dividend announcements, according to which, the NYSE consistently initially underreacts to dividend policy changes for the period between 1947-1967, and corrects the initial late reaction slowly, experiencing a drift (further underreaction). The performance however, is different depending on whether it involves a dividend increase or decrease, but does not change even when beta based returns are used in place of variance based returns, and is stable in other respects as well. These results are again supportive for the underreaction hypothesis, considering however dividend-based strategies this time.

In a more recent study, Klein (1990) tests whether the market overreacts the way De Bondt and Thaler (1985,1987) describe, under the assumption that overreaction will cause price reversals when news are released. He suggests two

[33] As we will see later however, it is not necessary for a drift to be caused by underreaction, but continuous overreaction could also lead to a price drift.

hypotheses to test for the formation period, and a third for the post formation period[34]. Acceptance of hypotheses 1 & 3 would be positive for overreaction, while if hypothesis 1 is accepted and 3 is rejected, this will be negative. CRSP data are used for 1977 to 1984, with IBES[35] EPS forecasts, while the methodology and the periods used are similar to De Bondt & Thaler's (1985). Results institute that extreme losers outperform extreme winners by 5.1% per month in the formation period, and for the next three Januaries they outperform them by 6.0, 5.8, and 3.8%, consistent with De Bondt & Thaler (1985, 1987), and Zarowin (1990). The first two hypotheses are supported, but results are also positive for the competing rational expectations hypothesis, and thus strong conclusions can't be drawn. With respect to the third hypothesis, analysts do not underestimate earnings of extreme losers, but they overestimate future earnings, when at the same time they do not overestimate future earnings for the extreme winner portfolio. Having accepted the first and rejected the third hypotheses, the results are clearly against the overreaction hypothesis. I am however somewhat sceptic about the consequences of the short period used (1977-1984) for the study. These concerns increase, when considering that previous studies have used longer periods, like for example De Bondt & Thaler (1985), who have considered a sample of fifty-six years (1926-1982). The study might thus be worth repeating for a larger sample period providing a test of the validity for the findings for a different and more generally representative period.

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[34]Hypothesis **A**) Earnings prediction errors at the beginning of each formation year are on average, positive (negative) for the poor (good) share price performers. Hypothesis **B**) During the formation period, revisions in analysts' earnings forecasts are on average, negative (positive) for the poor (good) share price performers. Hypothesis **C**) Over the post formation period, the average prediction error for the portfolio of stocks that perform poorly (well) over the formation period is negative (positive).

The same year, Lakonishok and Vermaelen (1990) also find post event abnormal returns due to underreaction. They use data on announcements & expiration dates, terms & outcomes of repurchase tender offers during 1962-1986 and daily stock returns & trading volume for NYSE, AMEX, and OTC firms. Several trading rules are tested and both parametric and non-parametric analyses are used. The results are initially positive for contrarian strategies, which outperform the value-weighted CRSP index by 23.11% for 3 to 24 months post announcement. However, controlling for both size and risk the figure is reduced to 8.76%; and braking down results by firm size, small firms experience reversals while large ones do not. The study concludes that an investor can make arbitrage profits by shorting past winners to buy under-priced firms. Two years later, the investor will have a substantial profit, especially if the firms are small firms with fewer specialists following their behaviour and thus a higher theoretical possibility of miss pricing. The difference here from other studies is that contrarian profits are not considered to be due to overreaction, but underreaction, because there is an observed drift in pricing, and investors initially underreact by under-weighting the news, and then correcting their mistake as new earnings announcements come in to light.

A year later in 1991, Mendenhall searches for evidence to support the assertions of the studies mentioned so far on post-earnings announcement drift[36], setting three questions for the paper to answer: (a) Do analysts underweight prevailing earnings information in forecasting future returns? (b) Do investors use analysts forecast revisions to revise their own expectations? (c) Do investors

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[35] Institutional Brokers Estimate System

systematically underestimate the persistence of previous forecast errors signalled by forecast revisions? Announcement dates, earnings, analyst forecast data, and daily common stock returns of 582 firms with revision dates between April 1982 and December 1986 are used. Abnormal returns are calculated and summed to obtain cumulative abnormal returns for each stock. The tests on the first hypothesis reject the null of no systematic relation between continuous earnings forecast errors, showing that analysts underweight current information underestimating the earnings forecast errors persistence. Consistent with Freeman & Tse (1989), and Easton & Zmijewski (1989), the null of the second hypothesis that there is no systematic relation between Value Line Earnings forecast revisions and the most resent forecast error, is also rejected. This implies a systematic positive (negative) relationship when revision and forecast errors have the same (opposite) sign, and that investors use analysts' revisions in order to do their own revisions. The third hypothesis tests the null of no systematic relation between earnings forecast revision and abnormal returns around subsequent earnings announcements, measuring the power of previous forecast errors and revisions over prevailing ones. The revision's factor is found to be significantly different than zero in the 1% level, and the null is again rejected, revealing a relation of earnings revisions and abnormal returns around subsequent earnings announcements. I believe that the results of this study do actually support contrarian strategies, given that investors underestimate earnings announcements, slowly revising their estimations in the future, causing a price correction towards fundamental values, and increasing (decreasing) the value of under (over) estimated stocks.

[36] The roots of his study can also be traced in Bernard & Thomas (1989,1990), Freeman & Tse

In another study related to analyst reaction to earnings information by Abarbanell & Bernard (1992), earnings per share and corresponding value line forecasts are used together with NYSE and AMEX (from the CRSP tape) quarterly price data on 178 stocks adjusted for stock splits and dividends between 1976 and 1986. The evidence agree with the previous studies on analysts underreaction to recent earnings information, but the difference here is that results are also consistent with a seasonal random walk. When the authors examine whether analyst forecast errors explain the post announcement drift, they find that the market is surprised by earnings news, and that abnormal returns are concentrated around subsequent earnings announcements. The important part of the paper is that although it finds the same results as De Bondt and Thaler (1990) for contrarian strategies, here stock prices respond to announcements later than analysts respond. This is due to transaction costs or to further underreaction on the already delayed reaction of analysts to these earnings announcements. So, underreaction is for once again considered to be responsible for return predictability and any profits delivered by it.

Michaely, Thaler & Womack (1995) analyse stock reactions to a different type of information, namely dividend policy changes announcements, considering both short and long-term reaction on NYSE and AMEX firms between 1964 and 1988 (they also use COMPUSTAT data for 1972 to 1978 on 235 initiation and 290 omissions). Excess returns are computed using four different proxies for the market portfolio, and the results indicate that the effect of omissions is quite larger than the effect of initiations. More specifically, results for the 3-day

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(1989), and Rendleman, Jones & Latane (1987).

period around the announcement show that firms initialising dividends experience a statistically significant increase of excess returns by 3.4%, when omissions cause a decrease of 7.0%. Testing the comparability of losers in their sample and De Bondt's & Thaler's (1985) sample, they find that although their losers are not as extreme, they are significant enough to expect reversals, which never come however, in-fact results are consistent with underreaction (post announcement drift is observed). The effect is not clear however and not strong due to the small sample used. Repeating tests for different benchmark portfolios, controlling for size & industry concentration, and changes in risk does not make any difference. However, an event-clustering problem is found, with results being extreme for the sub period 1975-1988 compared to 1966-1975. The clientele effect does not explain results since small volume changes are observed, and thus underreaction appears to be the most appealing explanation.

The review of the literature next looks at yet another possible source of information, namely repurchase announcements. Ikenberry, Lakonishok, & Vermaelen (1995) are interested in the market's reaction to open market share repurchase announcements. In an efficient market, such a signal should be incorporated in stock prices immediately, and no further future effects should follow, otherwise predictable profit opportunities may exist. The sample consists of returns and 1239 announcements of NYSE, AMEX and NASDAQ firms' intention for share buyback from January 1980 to December 1990. Results are obtained for both a short time-window around announcements and for a longer period, using two approaches with four different benchmarks each:

one based on cumulative abnormal returns, and one on buy-and-hold returns. They first look for short-run evidence expecting prices to adjust instantly if the market is efficient. Consistent with previous literature, they find that the initial reaction is just 3.54% of abnormal returns in the two days around the announcement, and normal there after, up to the 10th day, which shows possible underreaction. Furthermore they find that the smaller the firm the larger the abnormal returns[37] are; for example the abnormal returns are equal to 8.19% for the smaller 20% of firms, and 2.09% for the largest 20%, decreasing steadily as one moves from smaller to larger firms. They also report that investing in buyback companies produces a substantial abnormal return, and that even when estimating a cross-sectional regression of returns on size, B/M ratio, percentage of buyback, and price reversals; B/M is found to have the higher effect (controlling for overreaction). Controlling for take-overs, they find that a take-over increases profits but does not completely explain them. They also control for past buyback announcements to find that although they increase abnormal returns to 15% (compared to 11.3% for single announcement firms), they cannot explain results. The study concludes that the results are positive for market underreaction and negative for overreaction, the reason being, that the market responds with a drift to buyback announcements. Based on this, an investor employing a strategy that longs buyback firms and shorts non-buyback firms can make a profit.

Using a different method Jegadeesh & Titman (1993) test for relative strength strategies based on three to twelve month horizons for NYSE & AMEX data

[37] This should be expected, because the smaller the firm, the larger the information asymmetries are bound to be.

between 1965 and 1989. Forming portfolios based on the last six months, relative strength strategies earn on average 9.5% in the first year but lose half of it in the next year. Up to seven months after announcement, winners outperform losers; however for months eight to twenty the situation reverses consistent with many other studies e.g. Chopra, Lakonishok & Ritter (1992) that find initial momentum before overreaction. Using several formation and testing periods they show that relative strength strategies are profitable, with the best one being the one based on twelve months formation and three months holding. To decompose profit to its sources, two return-generating models are used, the first one to find the effect of systematic risk and firm-specific components, and the second to detect any lead-lag effects. The results indicate the possibility of profits being due to underreaction to firm specific information, and not to lead-lag effects. Furthermore, tests for beta and size effects indicate that although small firms appear to have higher abnormal returns, size or systematic risks do not explain profits. Results are significant even after considering a 0.5% one-way transaction cost. With respect to seasonality, there are profits out of January, but not in January where winners encounter mean loses of 7% (the smaller the firm the larger the loses). Another interesting finding is that twenty-four out of twenty-five Aprils exhibit abnormal profits, which average to 3.33% per April. Therefore, a relative strength strategy has results in the short run after thc announcement; while in the long-run losers outperform winners. In our opinion these results show that, either relative strength drives the market out of equilibrium temporarily with prices overshooting, or that investors underreact to short-run information but overreact on the long run.

What has just been described is a possible combination of both overreaction and underreaction in determining market behaviour, and this is what the literature review will analyse next, providing evidence in the next subsection of positive contributions of both of them towards contrarian profits.

2.6. Evidence supporting both overreaction and underreaction

Apart for the studies that are presented and discussed in this section, there are many others with similar results, which however will be analysed later because they have been grouped under a different category, namely that of strictly behavioural studies. For example, Barberis, Shleifer, and Vishny (1997) observe short-run underreaction and longer-run overreaction. Amir & Ganzach (1998) find overreaction (underreaction) to forecast changes (revisions), and overreaction (underreaction) is observed for positive (negative) forecast changes. Hong, and Stein, (1999), propose that the smaller the firm in question the stronger the short-run positive correlation and the long run negative serial correlation. Daniel et al. (1998), and Hong, Lim, and Stein (2000), work in the same line. In addition, Jegadeesh & Titman (1995) show that stocks underreact to common factors and overreact to firm-specific news, as shall be seen in the section related to negative evidence for the lead-lag explanation.

Dreman & Berry (1995) believe -in contrast to most of the authors in the previous subsections of the literature review- that overreaction and underreaction are not mutually exclusive. They propose "the miss pricing-correction hypothesis" (MCH), according to which, stocks are initially miss priced due to investor overreaction. More specifically, investors are initially overoptimistic for well-performing (high P/E) stocks and pessimistic for bad performing (low P/E) stocks; and two sets of events can take place after this initial miss pricing: either "triggering events" or "reinforcing events". The first are surprise good news for bad performers, and surprise bad news for good performers. This category of events should lead to investors revising their initial expectations asymmetrically (higher revision for losers than for winners). The second category of events would be good news for well-performing stocks and bad news for bad-performing stocks. These events should not affect expectations that much. The authors state that for their theory to hold, the absolute effect of the first set of events should be larger than the effect for the second set of events. Quarterly US earnings data on 1,331 firms for the period between January 1973 and March 1993 collected form the Abel Noser database and COMPUSTAT are employed. Annual and five-year holding periods are tested, and portfolios are formed based on the stocks' twelve month P/E multiples (a low, high, and a medium P/E portfolio are constructed).

The authors find that when good news are released, low P/E firms are influenced much more than high P/E firms[38], and that a year from the surprise, the effect on high P/E stocks is not different from zero. Bad news also have an asymmetric effect, which again is logical, since they should affect good firms more than bad firms. During the first quarter, surprises lead to returns of -4.17% and -18.49% for low and high P/E stocks respectively, and a year later the effect is cancelled out for bad firms, and is about -9.54% for good ones. Both good

[38] They expect this logically, because good news should impact bad firms but not good ones.

and bad news have an asymmetric effect in low and high P/E firms, tending to favour bad (low P/E) firms. The evidence is supportive for the authors' position on the absolute impact difference of "event triggers" and "reinforcing events", with the first having a significantly larger effects compared to the second.

To sum up, it can be said that the paper provides evidence of initial overreaction of investors that are very optimistic or pessimistic about high or low P/E stocks respectively. Surprise news lead investors to revise their expectations, but this reaction is characterised as slow, thus investors are underreacting. Therefore, investors make mistakes, which they tend to repeat, and the paper supports the existing evidence of initial overreaction and later price correction, which is however sluggish.

In the following year, Fama & French (1996) propose that the so-called anomalies suggested by other papers, are not actually anomalies, but are considered as such due to the inability of the traditional CAPM to capture real risk (beta incapability). As an alternative, they suggest a three-factor model, which should capture these so-called anomalies. According to the model the expected return on a portfolio above the risk free rate can be explained by three explanatory variables: the excess return on a proxy used as the market portfolio, the return difference of a small stock portfolio and a large firm portfolio, and the return difference of a low B/M ratio portfolio from a large B/M ratio portfolio. They test for all NYSE stocks that have COMPUSTAT data for July 1963 to December 1993, forming portfolios ranked based on their B/M, E/P and C/P ratios, and on whether they are strong or weak (based on accounting ratios and past sales growth). Their results are against short run overreaction, since there are no price reversals and losers remain losers and winners remain so, consistent with the underreaction hypothesis indicating that prices may adjust with a drift. The only case that the model can not completely explain overreaction, is for the period 1963 to 1993, when considering 60 to 13 months of prior returns, and the next four years in the future for post returns. Nonetheless, when considering the period 1931 to 1963 stronger return reversals are captured, and thus the model can be considered as able to explain movements of portfolios formed on past returns. The reasons for the return behaviour observed in the future are the differences in B/M ratios E/P ratios of different firms connected with market premium. Another explanation for the differences can be: miss prising by investors that overreact, overvaluing (undervaluing) growth (value) stocks, or it could mean that although the market is efficient, data snooping might affect results. The model is unable to explain positive serial correlation in short run returns, which might be due to an initial market underreaction that is reduced as time goes buy. In this case, profits can be made buy applying other strategies based on past returns and only, implying an inefficient market. In addition, I believe that investors may overreact to long-term information and underreact to short-term information, consistent with Poterba & Summers (1988), making both contrarian and relative strength strategies profitable when based in different information periods. In any case, the multi-factor model by Fama and French is very important, because it captures a lot of information and explains most of the contrarian profitability that could not be explained. We thus believe that is a very useful tool for our purposes, and should be used as an alternative to the single-factor model.

2.7. Other explanations for Contrarian profitability

As has already been discussed in the introduction, there are two main strands in the literature for return predictability and contrarian strategies. The first one proposes explanations that rule out any abnormal contrarian profitability, and does so in an efficient market context, while the second strand considers markets as being inefficient, and contrarian profits as genuine. The overreaction and underreaction hypotheses that have already been analyzed belong in the second strand, but were purposely analyzed first and separately due to their importance for the thesis. There are however, other issues that literature must address before any conclusions are reached; and in the remainder of our review, the reader will be presented with the scientific discussion on these issues.

2.7.1. Contrarian profits under Efficient Markets

2.7.1.1 Risk proposed explanation for contrarian profits and predictability

Some studies suggest that contrarian profits are due to risk miss measurement per se, or risk changes between different periods, for which researchers have not controlled. A study by Loughran & Ritter (1996) for example suggests that both risk and overreaction can explain results (taking into account for risk however, will normally reduce the magnitude of abnormal profits). It is thus easy to understand that the risk explanation of contrarian profits is usually against both over- and underreaction, at least up to the fragment of abnormal returns behaviour it explains; since the more profitability risk explains, the less is left to be explained by the above anomalies.

In a very influential paper -given that its methodology is applied in many other studies for contrarian strategies- Chan (1988) criticizes the De Bondt & Thaler (1985) paper, and argues that the excess returns in that study are not due to overreaction as the authors assume, but are excess risk premiums. In order to enable comparability with the previous paper Chan uses the same methodology and sample, but also collects another sample with less restrictions, which consists of firms that are less established. He suggests that if the price of the stock is a good proxy for risk, then losers should be safer in the beginning (having a low price), but riskier in the future when their price increases; and that the opposite should hold for winners. Consequently, if someone uses rank period betas to run regressions for the post-rank (test) period, he will get biased estimates. Another argument he puts forward based on Fama & French (1986), is that size cannot explain part or all of the results.

He studies risk and performance for both rank (formation) and post rank (holding) periods using a regression with dummy variables for the two periods, their betas, and their mean abnormal returns. He finds that losers (winners) experience large abnormal negative (positive) returns in the rank period, and as a result the arbitrage portfolio loses 4.56% for the first sample and 5.87% for the second[39]. With regards to the test period, the arbitrage portfolio exhibits small abnormal returns that are not significant, while the loser portfolio suffers some losses that are lower though than the ones that winners experience. The second sample shows reversals for losers, and more than double arbitrage abnormal returns, which however are statistically insignificant.

With respect to risk, losers are less risky in formation and more risky in the post-formation period, and their betas increase in sixteen out of eighteen cases, eleven of which are statistically significant. On the other hand, winner betas decrease in the same sixteen periods, of which nine are statistically significant. Intuitively, because of the two previous findings, the arbitrage portfolio betas also increase. The results are similar for both samples used. An interesting discovery is that results are sensitive to different specifications of abnormal returns: using a different method than De Bondt & Thaler to calculate returns for the arbitrage portfolio, Chan finds 5.84% three-year abnormal returns compared to 9.86%. Concluding, he suggests that: "loser betas need not be larger than winner ones all the time, but for them to be more risky, they need to be higher just when the expected market premium is high". A year earlier however, De Bondt & Thaler, and a few years later Chopra et al. (1992) and Dissanaike (1997), respond to Chan's arguments and show that time-varying risk does not explain predictability; while other papers as will be seen (for example Gaunt 2000) provide evidence that support Chan's assertions to some extent. I believe that it would be interesting to compare the method that Chan proposes with other methods taking into account for changes in risk, in order to access its ability to capture such changes.

Ball & Kothari (1989) build on the work of Poterba & Summers (1988), and Fama & French (1989), and expand it in the sense that they test if the negative serial correlation they observe is due to risk differences over time, taking research a step further. They propose that, either changes in expected returns, or

[39] The two samples are the one that follows the De Bondt and Thaler restrictions, and the other

market miss pricing (possible overreaction) are at work, and they also test how risk changes affect De Bondt & Thaler (1985,1987) results. Monthly CRSP data are used for the period 1926 to 1986 to form twenty portfolios on the beginning of each calendar year based on ranked total returns of the previous five years, or firm size. They generate five-year ranking and post-ranking periods, and then calculate each stock's buy-and-hold returns for each year in the two periods. Abnormal returns and systematic risk for each portfolio are calculated using fifty-two years' of returns using the market model to find them, for each of the ten event years, and to detect systematic risk shifts over time.

The results reveal correlation coefficients between the formation and post-formation periods that are significantly negative, which is consistent with the overreaction hypothesis. Believing however that results are due to risk; they look into betas for the two periods, observing that extreme losers become more risky in the post-formation period, with their beta increasing by 78%, while extreme winners on the other hand experience a reduction of 57% in the second period, becoming less risky. The authors argue that this is the reason of the observed change in expected returns, since more than half of the portfolios experience significant beta changes between the two periods. When constant risk is considered, there is significant negative correlation between returns ranging from -12.2% to -13.7%, when however beta is allowed to change, then abnormal returns are reduced to 2.6% annually, and 97.4% of the abnormal returns are explained by the risk differential. They find that the size effect can explain a small portion of findings, and the results for size ranked portfolios are

is less restrictive as we discussed.

on average in line with the previous, been consistent with the miss pricing hypothesis, but less volatile. When they look into sub-periods, they find again the same results, but the pattern is inconsistent with the miss pricing hypothesis. The paper shows the importance of allowing risk variation in order not to bias results, and if the findings of the paper really hold, then the market is efficient and there is no overreaction, but actually, there is an effect of risk changes through time. Put simply, losers make higher returns than in the past because they are more risky, and the opposite holds for winners.

The discussion however heats up and many scientists disprove the findings for the risk differential explanation. Jegadeesh (1990) that was discussed in section 2.2 discards the risk explanation, while Brock, Lakonishok, and Le Baron (1992) that were also discussed earlier, show that risk as usually perceived (related to beta) does not describe asset returns. Zarowin (1990) uses Chan's methodology but finds opposite results, disproving him, whilst Gishan Dissanaike (1997) also disproves the explanation using both Chan's (1988) and Ball & Kothari's (1989) methodologies. Ball, Kothari, & Shanken (1995) who suggest cautiousness when interpreting both Chan's and De Bondt and Thaler's results find similar evidence. The above mentioned studies are not the only ones that disagree with the risk variation explanation; and the thesis will now analytically present three other studies that find, among other things, evidence against the risk differential explanation.

2.7.1.2. Evidence against risk and changes in risk, as an explanation for return predictability and contrarian profits

De Bondt & Thaler (1987) come back to respond to the severe attack their 1985 article suffered[40], and among other things they consider the possibility that results are due to differences in (risk) in terms of changing CAPM betas and they also re-evaluate the overreaction hypothesis connected to the January effect and the size effect. They use data from 1926 to 1982 and estimate 120 monthly market-adjusted excess returns, using an equal-weighted average of all NYSE monthly stock returns as a market proxy. The procedure is repeated ten times for ten-year periods[41] each time, and fifty portfolios are created based on formation period cumulative excess returns, ranked from extreme winners to losers. They find that most of the loser test period[42] abnormal returns are in January, with winners also exhibiting positive excess returns, although smaller. In January losers make long-run abnormal returns of 7.9%, whilst winners have short run loses of 1.8% but remain long run winners with abnormal returns of 3.5%. Most of the abnormal returns for losers are due to pure price reversals.

To test for changes in risk they regress annual stock returns on the market risk premium using the CAPM. In contrast to their 1985 results, losers are more risky than winners are, but the difference is small to explain the effect. Then they test allowing for two betas, a 'bull' and a 'bear' market beta, and find that past losers are more aggressive and make more in bull markets and are less

[40] They clearly state that the explanations given by them and contrasting authors are not mutually exclusive, they might work at the same time.
[41] Five years formation and five years testing period.
[42] Returns are very high in January for the formation period also.

risky and lose less in bear markets ($beta_{bull}$=1.388, $beta_{bear}$=0.875), than winners do ($beta_{bull}$=0.993, $beta_{bear}$=1.198). These results disagree with the risk change hypothesis, according to which losers should be riskier than winners to make excess returns. They also find that small firms form extreme return groups, but size does not explain results. Finally, testing overreaction to earnings for 1965 and 1984 they find positive evidence for it, since both winners and losers experience reversals, which are however much higher for losers than winners.

The above paper shows the winner-loser effect not to be due to CAPM betas and systematic risk changes as Chan, and Ball & Kothari in the previous section suggested. Furthermore, they also find that size incorporates only part of the anomaly. The results are positive for the overreaction hypothesis, nonetheless the dispute continues, and a decade later the debate persists.

For example, Richards (1997) based on results of Chan, Karolyi, and Stulz (1992), looks once again into the whether De Bondt and Thaler's (1985) results are due to overreaction or due to risk differential as Ball, Kothari, and Shanken (1995) argued. He applies the De Bondt and Thaler (1985) methodology to end-of-month data on 16 national markets[43] between 1969 and 1995, and finds like many others a twelve-month lag before the contrarian strategy delivers any profits. The strategy earns 6.4% of abnormal returns p.a. that start fading out after three years, becoming 5.8% and 3.4% for the fourth and fifth year respectively. More interestingly, total risk is calculated in the form of the three-year return standard deviation, and delivers no evidence that losers are more risky than winners in the testing period. To test for the possibility of contrarian success been due to risk changes between formation and testing periods, he compares the differences in changes of losers and winners exposure to two factors: a) The excess returns of the MSCI index, and b) the excess dollar return on a G-10 countries trade-weighted index of short-term assets. Results not only disprove the suggestion that losers are more risky than winners in the sample period, but show that most probably the opposite holds. Based on Lakonishok, Shleifer, and Vishny (1994), he also tries to observe whether there are any differences in the contrarian portfolio's performance in different states of the economy, and the results indicate that although losers outperform winners in both possible states of the economy, they do not suffer any extra exposure to risk than winners do in downturn states. The author then tests for the January effect, to unearth that seasonal effects do not explain returns, since only 5% of the total 23.1% of the abnormal returns come in January. Testing for the size effect, he creates two country groups (small and large[44]), and discovers that contrarian strategies are more profitable for the smaller market group with losers having 32.4% higher returns than winners, compared to just 22.5% for the larger group. However, he does not conclude that the phenomenon is narrowed to small markets, since it is observed in large ones as well. To summarize the vast amount of findings, the results show that risk differential does not explain performance differences. Of course, results may be affected by the small sample (16 national markets equivalent to 16 stocks in national tests). I also believe that some fragment of the return differential is explained by size,

[43] Australia, Austria, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, UK, and US markets.
[44] UK, Japan, Canada, Germany, France, Australia, Switzerland, and US form the large group, with the rest forming the other.

and I disagree that January represents a small portion of the returns, because the two first days of January returns represent 21.65% (5% out of 23.1%) of returns from a total of almost 1100 days in each investment horizon. Provided results are not affected by imperfect integration then the evidence is also against market efficiency.

Lakonishok, Shleifer & Vishny (1994) search why value strategies outperform glamour ones. Value and contrarian strategies both short good past performers to long bad past performers, and their only difference is that value strategies are based on certain value ratios and not on past returns. They use data for AMEX and NYSE firms[45] for 1963 to 1990 and investment horizons up to five years. Results show that value stocks outperform glamour ones significantly -using ratios like B/M, C/P, and E/P to create portfolios- by a mean of 10 to 11% per year. Repeating tests for the 50% and 20% of the largest firms does not change results but deflates them. Extensive tests show that reversals leading to contrarian profits are entirely due to upward (downward) revisions of the value (glamour) stocks' growth prospects. The results of the last study and the previous ones are clear-cut positive evidence for the overreaction hypothesis, and show that risk is not the answer for contrarian profits.

Nonetheless, in a more recent study, Doukas et al. (2002), provide solid evidence that is contrary to the findings of the above paper, suggesting that the superior behaviour of out-of-favour stocks cannot be explained by excessive pessimism about future growth in earnings.

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[45] They disregard the first five years of data for new firms to avoid look-ahead bias.

2.7.1.3. Bid-ask biases explanation for contrarian profits

Another important explanation against return predictability, and against overreaction as the cause of negative serial correlation is that of the bid-ask bias. More specifically, supporters of this explanation suggest, that as data are collected, one might collect bid, then ask prices, then bid and so on, and although the true price does not change, the collected prices will look increasing and decreasing all the time around the true price mean, and the false impression of negative serial correlation is then created. If bid-ask biases explain results, the efficient market hypothesis could hold.

Kaul & Nimalendran (1990) question whether bid-ask errors or overreaction is responsible for contrarian profits given that previous studies use data that don't disconnect overreaction and bid-ask bias. The National Market System (NMS) created in 1982 enables the authors to disentangle the effects from one another, because it contains bid and ask prices. Daily CRSP data for NASDAQ/NMS firms for January 1983 to December 1987 are used. Estimating daily autocorrelations based on transaction prices, they find reversals. Bid-to-bid returns however, indicate that a portion of these is due to the bid-ask bias. More specifically, returns are positively correlated for all except the first week, which however they link to the weekday return variance been less than the weekend one and not due to overreaction. The bid-ask error component is found to explain over 50% (23%) of the small (large) firm variance, and the writers propose that there is no overreaction and that reversal are due to lead-lag relations and bid-ask errors.

Kaul & Gultekin (1997) also propose microstructure effects behind all or part of the results, especially bid-ask spreads. They use weekly data on NASDAQ stocks for 1985-1989 and for AMEX, NYSE stocks for the period 1990-1991. They first estimate abnormal returns controlling for size but not for bid-ask biases, and find that contrarian strategies yield statistically significant profits, part of which however are due to positive autocovariance and not due to price reversals. More specifically, 27% of NYSE & AMEX, and 50% of NASDAQ profits are explained by positive autocovariances, while overreaction explains only a small part and not all profits. Next they re-estimate profits using bid returns to avoid the bid-ask bias, to discover that for NASDAQ all profits are owed to the bid-ask bounce and that for AMEX and NYSE half -on average- of the results are due to bid-ask errors. They also find that even for brokers or top corporate clients that have the lowest transaction costs, short-term contrarian strategies do not yield any profit after transaction costs are included in calculations. In NASDAQ, overreaction has no explanatory power, while for AMEX and NYSE overreaction explains at most 50% of results, profits however disappear after very low transaction costs are imposed. Bid-ask biases explain the rest of the results. I believe however that results are not strong because they are related to a very small period and number of firms. Furthermore, there is always the case that bid-to-bid data are available for fewer firms than return data are available for, and this might be the reason for the different results and not bid-ask biases per se.

2.7.1.4. Evidence against the bid-ask biases explanation

Loughran & Ritter (1996) use NYSE and AMEX data between 1928 and 1985 to form portfolios based on holding-period returns (HPR). More specifically, the firms with the highest HPR form the extreme winner portfolio, and the firms with the lowest HPR form the extreme loser portfolio. Two methods are employed for selecting winners and losers: one that is based on CARs and one that is based on prior buy-and-hold returns. They find that the buy and hold method provides a better firm classification in to portfolios, but apart for that, there is no other obvious difference between the two methods.

Evidence agree to some extent with Conrad & Kaul (1993), but overstate the log of the price ability to explain returns. Furthermore, they find that De Bondt & Thaler's (1985) results are not biased due to use of CARs, since the bid ask bias is cancelled out by the lack of compounding. They suggest though that some of the loser abnormal returns are due to overreaction as De Bondt and Thaler have suggested, and some is due to risk compensation consistent with Chan (1988), and Ball and Kothari (1989). They finally suggest that when a portfolio's stock selection is done based on a single factor, then its effect to returns is overstated. The important finding however is that overreaction and risk, but not the bid-ask bias explain De Bondt and Thaler (1985) results.

A large number of studies agree with the above findings, and support that predictability in not primarily a misperception that is induced by the bid-ask bias. For example, Jegadeesh and Titman (1995) also find for the US that the bid-ask bias does not affect return predictability and contrarian profits, and that overreaction explains findings. In addition, Loughran & Ritter (1996) use NYSE and AMEX data for the period 1928 to 1985, and find that the bid-ask bias does not explain predictability and profits, but risk & overreaction do. Based on these studies and on the thesis suggestions in the last few sentences of the previous subsection regarding the possibility of different stocks in the closing and the bid prices samples, one can understand that no definite conclusion can be reached, and the presence of the bias must be judged independently in each case, for each market, each sample, and sample period.

2.7.1.5. Short-term market illiquidity proposed explanation

Another possible explanation for results might be short-term market illiquidity as Jegadeesh and Titman propose in their 1995 paper. Lehmann (1990) tests the EMH using data on all AMEX & NYSE firms between 1962 and 1986. He creates zero-cost portfolios that are short in winners and long in losers, suggesting that if the EMH holds, profits should be zero on average and if results are other than zero, then the portfolios will produce profits due to speculative fad driven overreaction. The first results reject the EMH, since profits are made even with large transaction costs, and loser (winner) returns are positive for 65-70% (more than 50%) of weeks. The arbitrage portfolio profits 85-94% of weeks depending on the investment horizon, and profits by 100% for the twenty-six week horizon. On average, the winner (loser) portfolio has losses (profits) for the coming week, which are reversed (reduced) during the following four weeks. The little persistence of the reversals cannot be due to longer-run market efficiency, and as the author proposes, price reversals are due to short-term market liquidity inefficiency, caused by the inability of market makers to meet short-run demand from impatient traders. The study focuses on a shorter horizon than De Bondt and Thaler (1985) do, because over very short horizons (even if there are changes in the long run) systematic changes in fundamental values should be insignificant in an efficient market. The problem with this strategy is that it probably suffers from bid-ask spread, lagged reaction and price pressure effects, which are unfortunately not considered.

2.7.2. Explanations under an inefficient market context

As has already been discussed, a large proportion of the literature in return predictability and contrarian thematology does not support the notion of market efficiency. Overreaction and underreaction belong in this context, but because they are central to the thesis, they have already been discussed. Nevertheless, there are some more anomalies that have been employed to explain market inefficiency, according to which, investors can profit based on past information regarding price, returns, profits, and size. This should not be the case in an efficient market where no one should make profits based on past information, and any returns should be connected with the systematic risk of the instrument the investor holds. The discussion commences with the well-known size effect in connection to the overreaction hypothesis.

2.7.2.1. Size proposed explanation for contrarian profits

Zarowin (1990), not convinced by De Bondt & Thaler's (1985) explanation for predictability, endeavours to establish that size and/or January effects and not overreaction, are behind contrarian profits, based in a previous paper where he had already shown that losers are smaller than winners. First, he replicates the De Bondt & Thaler (1985) paper to uncover whether risk and seasonality explain abnormal profits. He finds that although losers are more risky than winners are, and there is a strong January effect, these are not large enough to explain abnormal returns. Here Zarowin also responds to Chan's (1988) suggestions about risk, using his method but not supporting his findings, since contrarian profits are not explained by time-varying risk. At a second stage, Zarowin creates five different size groupings and five subgroups based on performance in order to unveil the relationship between these two attributes (e.g. he compares small winners with small losers performance etc). He finds that losers outperform winners only in January, while size is able to explain results at all other times. At the final stage of his study, he seeks an answer as to whether the January effect is pure or related to investor overreaction in the strategy's first month. He repeats tests not starting at January but six months later; if the initial difference in January is due to overreaction, then he should now detect overreaction in the new initial month of July, otherwise if it is a downright January effect, past losers will still outperform winners during January. Sadly for the overreaction hypothesis there is no evidence of a July effect but there still exists a January effect. He also shows relevant to the size effect again, that when losers are smaller they outperform winners, but when winners are smaller they outperform losers. Intuitively, these results are again negative for overreaction and positive for the size effect, because if results are due to the overreaction phenomenon, losers should outperform winners no matter the size differential.

This paper set the discussion for the size effect in contrarian strategies, being for the size explanation, the equivalent to De Bondt and Thaler's (1985) paper for overreaction. Conrad and Kaul (1993), Ball et al. (1995), and Richards (1997) however disagree with the explanation as the literature review shows. Nonetheless, the findings are well argued, cross-examined, and supported by the next study.

Clare and Thomas (1995) follow up the work of Zarowin (1990) and study overreaction for the UK, employing end-of-month data, adjusted for dividends on a random sample of a maximum of 1000 UK stocks for the period between 1955 and 1990. The results for twelve-month horizons show momentum, but for other horizons, they are consistent with overreaction exhibiting annual abnormal returns for the arbitrage portfolio of 1.7% for the two-year and 1.57% for the three-year period, consistent with other studies, but quite smaller in magnitude. Next, based on Zarowin's (1990) evidence that overreaction is a manifestation of the size effect, they control for size, ranking stocks based on prior performance and size. The results for the twelve-month horizon show no size effect, but for the twenty-four month holding period, small firms outperform large ones, however results are statistically significant only for the second smallest loser versus the second largest loser (although large firm betas are higher than smaller ones). For the thirty six-month holding period results are same on average and significant only in one case again (fourth smaller versus fourth largest loser). Testing for seasonal effects using a dummy variable in an OLS regression, delivers weak evidence for the seasonal effect.

In our opinion, the results of this paper are in most cases statistically insignificant, making it difficult to accept size effect as a solid explanation. In addition, results are in general of such a small magnitude, that it's a debate whether any economically significant profits can be made, especially when considering transaction costs as well. The market used must definitely be reconsidered with more data (not only 1000 stocks) for more solid results.

2.7.2.2. Evidence against the size proposed explanation

Using UK data as in the previous study, Dissanaike (1997) tests the overreaction hypothesis for firms in the FT 500 Index for the period between 1962 & 1991, forming ten portfolios based on rank-period excess returns using stocks with no missing values for the previous 4 years, and holding them for the next four years. Returns are defined using two different methods: a buy-&-hold (BH) and a rebalancing strategy (RB). Results are significant for all testing periods (apart for the two first of the BH strategy), and losers outperform winners by 100% four years post formation. There is also an asymmetric effect again like De Bondt and Thaler (1985) first find, and price reversals are larger for losers than winners; Dissanaike also finds a magnification of profits in January. When using the RB method, results are stronger and significant at the 1% level except for the first testing period; with loser portfolios outperforming the winner ones by 137%, four years post formation. Dissanaike's regression analysis also suggests that losers are less risky than winners, consistent once again with Be Bondt and Thaler and against Chan (1998) and Ball and Kothari (1989). More specifically, even after adjusting for risk, abnormal returns are large and significant at the 5% level. Adopting Ball and Kothari's (1989) approach, both losers and winners betas jump upwards, with winners beta always jumping higher than the loser's one does, while the arbitrage portfolio's return is 11.74%. Tests are repeated for other periods, delivering initial momentum and then reversals using 24month-ranking period, which in conjunction with the findings of the previous study, provide a further incentive to test for the UK using shorter horizons, considering size and both over- and underreaction.

The results that Dissanaike finds in this study are consistent at least with respect to the size effect with most other studies, which also find that size either does not explain results, or explains a small part, but not all of the results. Examples of such studies that have already been analysed and thus just mentioned here are: Fama and French (1988), Ball and Kothari (1989), De Bondt and Thaler (1990), Richards (1997), Bowman and Iverson (1998), Chopra et al. (1992), Pettengill & Jordan (1990) etc.

2.7.2.3. Cross-sectional explanations for contrarian profits

Lo & Mackinlay (1990) argue that part of contrarian profits do not come from price reversals but from forecast ability due to delayed reactions across stocks. Of course the issue of lead stocks has already been mentioned by others, see for example Philippatos and Nawrocki 1973. More specifically, Lo and Mackinley suggest that if stock 'a' has abnormal profits (loses), and another stock 'b' follows, having abnormal profits (loses) in the near future, picturing the movement of stock 'a' with a lag, then one can sell (buy) stock 'a' which is a winner (loser) and buy (sell) stock 'b' that will become, but is not yet a winner (loser). They use daily CRSP data for NYSE and AMEX stocks, for the period 1962 to 1987. They find strong positive autocorrelations for equal-weighted and value-weighted indices, and weak negative autocorrelations for individual stocks. They construct three size-based portfolios, and study separately the effect off price reversals (own autocovariances) and lead-lag effects (cross-autocovariances), and find that the predictability is half due to the first and half due to the second, both being statistically significant at the 1% level in the first lag but not the rest. The profits however, are significant even up to the fourth lag and higher for smaller quintiles, agreeing with most of the relevant literature so far. They conclude that a lead-lag relationship is responsible for most of the profitability, and introduce a new era in contrarian strategies. One problem that the authors admit is survivorship bias. Another problem as I believe is the creation of size-sorted portfolios whose composition is stable over time, which induces other biases that might affect results, since firm size and risk change over time as we know.

Chordia & Swaminathan (2000) build on the previous article's evidence that small firms follow large ones. They look into the relationship of trading volume and prediction of daily & weekly returns based on cross-autocorrelations, for NYSE & AMEX common stocks between 1963 and 1996, forming 16 annually rebalanced portfolios based on size and trading. Results are consistent with underreaction because some stocks underreact and adjust slower than others to new information. More specifically, they show that after controlling for size and thin trading, high volume stock returns lead low volume ones because they adjust faster. One can make arbitrage profits using trading volumes and can sell (buy) a low volume stock no matter of its present behaviour, based in the fact that the connected larger stock has done worst (better) than it did. However, the results may turn to be economically insignificant if transaction costs are to be considered, and one should be careful in interpreting them.

2.7.2.4 Evidence against cross sectional explanations

In a very important study, Jegadeesh & Titman (1995) respond to Lo and Mackinley's (1990) suggestion that contrarian profits are due to lead-lag relationships between stocks. They study short-run contrarian strategies like Jegadeesh (1990) and Lehmann (1990), and with the aid of an asset-pricing model separate stock reactions to common factors[46] and firm-specific news. The paper uses weekly data on all NYSE & AMEX stocks that have 260 continuous observations between 1963 & 1990, excluding those with prices lower than one US dollar[47], which leads to 1987 firms for each week on average. One of the things that make the work important, is that it shows that Lo and Mackinley's (1990) decomposition can hold when stocks react at all times only instantly or only with a lag, but not both. This reduces the validity of the Lo and Mackinley (1990) results, but not the importance of their suggestion on the lead lag effect (which as we said introduced a new epoch for such studies).

[46] By definition, lead-lag effects are connected to common factors only, and measuring common factor profits is like measuring the lead-lag phenomenon contribution to contrarian profits.
[47] These are the stocks, which are most likely to be affected by bid-ask error biases.

Following Lo and Mackinley's strategy, results indicate that smaller firms have larger weekly contrarian profits per dollar long (2.43% for small and 0.6% for large stocks), but the lead-lag effect can't be exploited by contrarian strategies. Using a single-factor model to regress each stock's return on the CRSP value-weighted index returns, the results show that small firms react with a delay while large ones react almost instantly. They then examine the length of the contribution of the lead-lag phenomenon to contrarian profits by looking in cross-sectional covariances of present and lagged beta values. They find that delayed reaction can explain about 1% of contrarian profits compared to overreaction to firm specific news that explains much more.

Allowing for time-varying factor sensitivities, only 3.89% of profits are attributed to lead-lag and most profits are related to firm-specific overreaction. They also control for non-synchronous trading and bid-ask biases by skipping a day between formation and holding period, although this method has been disproved by Kaul, Conrad, & Gultekin (1997). The profits are still significant and again overreaction to firm-specific information explains almost all profits. Furthermore, using bid-to-bid data after 1983 on NASDAQ firms to control for bid-ask biases they obtain contrarian profits of 1.86% per US dollar long, and overreaction to firm specific information is again responsible for most profits.

According to results, stocks underreact to common factors and overreact to firm-specific news as Lo and Mackinley suggest, but most contrarian profits are owed to the later, while the first can explain a very small portion at best. I believe however that their results are very sensitive to the common factor employed, and the lack of explanatory power of the common factor might be due to using either the wrong factor, or only one of the relevant factors. It would thus be very interesting to search whether using a multifactor model instead of the single-factor one affects results, especially with regards to the common factor(s) contribution.

Jegadeesh & Titman (1999) test the data mining explanation for momentum gains by replicating their (1993) results, using an out-of-sample period (1990-1997) for NYSE & AMEX firms. Stocks are ranked in ten equally weighted overlapping portfolios each month, based on past six-months return, and are held for six months. Results confirm their 1993 ones; for each sub period and the total period winners outperform losers, this however would not be unexpected for six-month investment horizons as seen so far. They also find that although contrarian strategies work in Januaries (losers outperform winners by 2.92% and 1.21% for their 1993 and 1999 samples respectively), momentum strategies do better out of January with profits of 1.47% and 1.20% for the first and second sample respectively. In addition, winners are larger and less risky than losers when considering the Fama French three-factor model.

Testing conflicting behavioural theories, they find that momentum strategies are profitable only up to twelve months in the holding period, while return reversals are observed after that, and for up to four years. Furthermore, when they extend the period by another year, results are similar, and do not change even when they separate the sample in two sub periods: 1965-1980 & 1981-1997, although there is some difference in the magnitude of the returns of the two periods.

They show that Conrad and Kaul's results are incorrect due to overestimating the contribution of cross-sectional differences, and that their simulations are also biased because they pool returns in a way that makes it possible to draw an observation in both formation and testing period. When the authors control for the previous bias, the results are different, and consistent with behavioural models' overreaction. Almost all of the reversal though is on the final year, and should be treated consciously. The profits are due to the returns time series and not to cross-sectional dispersion, thus the lead-lag phenomenon is unable to explain results. Contrarian long run profits are due to overreaction, which however can be described as being delayed since it takes time for it to occur.

2.7.2.5. Low-priced firm explanation for contrarian profits, positive and negative evidence

A study related to the low-priced firm explanation for contrarian profits is that by Conrad & Kaul (1993), which is also important -provided it is correct, which off course will mean that Fama 1998 is incorrect- because it has crucial implications for all event studies. More specifically, their work suggests that cumulative raw or abnormal returns will deliver results that are biased upwards[48], and thus holding-period returns of long time intervals must be used as an antidote. Loughran and Ritter (1996) later show however that this is not the case (see section 2.7.1.4). Conrad and Kaul use data on NYSE stocks for the period between 1926 and 1988, and first apply the De Bondt & Thaler (1985) methodology for, and out of January, and then re-estimate using holding period returns. Using the first method, results agree with De Bondt & Thaler and even when excluding January the pattern is the same. They observe however that the most extreme cases of profits or loses involve extremely low or highly valued firms, suggesting that low-priced firms could explain part of the results. Using buy-and-hold returns, price reversals are fully explained by the January effect, the arbitrage portfolio (losers minus winners) looses 1.7% compared to gaining 12.2% when the cumulative method is used. Then they assess the possibility of a small firm effect being at work as shown by Zarowin (1990) but find no evidence to support this scenario. Estimating regressions of cumulative returns on the price and market value of winner and loser portfolios, the evidence is consistent with their bias hypothesis. At the same time, estimating regressions for holding period returns, any price reversals in January are not due to overreaction but related to under-priced firms.

Ball, Kothari and Shanken (1995) build on Conrad and Kaul's (1993) paper examining the problem of measuring long-run contrarian performance, focusing on both raw and risk-adjusted abnormal returns. Monthly CRSP, AMEX and NYSE data up to 1991 are used under the De Bondt & Thaler (1985) methodology, the only difference being that this study also considers AMEX stocks[49]. For December-end raw-returns, consistent with contrarian theory, losers outperform winners by 91%, in both the first and second half of the sample. Nevertheless, observing the median values and distribution in general,

[48] Cumulating short-term returns for longer horizons cumulates not only real returns but also the upward bias of the short-term returns, as they support.

[49] This should not be a problem for overreaction, since these stocks are of smaller size and are followed by analysts less than the NYSE stocks, something that should enhance overreaction probability. Also, the tests are repeated later for only the NYSE stocks, not giving different results however.

it seems that the effect is mostly due to lower priced stocks. They then test whether a contrarian strategy profits no matter the month that the strategy is initiated, because Roll (1983), Lakonishok and Smidt (1984), Keim (1989) and others suggest that this is not the case and the strategy is more profitable when beginning at December-end. Using June-end portfolios they get loser portfolio mean returns that are 31% lower compared to when using December-end, and the contrarian portfolio returns are down by 34% while for winners the effect is close to zero again. Repeating the experiment for August-end portfolios, they unearth similar results, and suggest that the December difference is due to microstructure factors described above, and there is no overreaction.

Due to the relationship between prices and loser returns, they use both regression and price-quartile statistical analysis[50]. Using the second method, for December-end portfolios, lowest-priced losers have a mean return of 357%, which decreases progressively when moving through quartiles (113%, 96%, and 85%). When running the tests for June[51] they find that the difference between the two periods is confined to lower-priced firms. For example, the difference in quartile 1 between the two periods is 86%, and for the last quartile (higher-priced firms) the difference is only 2%. A $ 1/8 adjustment again affects losers by 86% (271% drop from 357%) for December based portfolios, and 55% for June portfolios. Excluding stocks priced lower than a dollar, mean returns drop to 116% from 163% for December and 105% from 132% for June-end portfolios, and controlling for the market index effect[52] leads the average loser

[50] They divide loser portfolios in to four quartiles based on price starting from low to high.
[51] For June results are 254% for the first quartile, and 110%, 85% and 83% for the others respectively.
[52] Price and Index positive relationship in the long run.

return to fall by 23%. Estimating regressions for extreme loser and winner returns annually, the evidence is positive for both overreaction and low-price effects. Controlling for size, they find that contrary to Zarowin's (1990) suggestion, it has no explanatory power. Allowing betas to vary leads to even lower abnormal returns, and when excluding low priced stocks (bellow 1 US $), December (June) portfolios abnormal returns are reduced to 0.1% (5.3%).

Baytas & Cakici (1999) test overreaction using arbitrage portfolios based on past performance, price, and size, for the first time simultaneously for Canadian, UK, Japanese, German, French, Italian, and US markets; making it easy to compare results. Data on five-year averages and annual returns of all countries are collected from the "Wordscope Disclosure Database" for 1982 to 1991. Consistent with the overreaction hypothesis loser (winner) portfolios outperform (under-perform) the market portfolio in the next one, two and three years for all countries except for the US, and Canada; and three-year arbitrage returns are positive and significant except for the US market. The average return for the arbitrage portfolio ranges from 12.4% in Canada to 94.5% in Japan. They also find an asymmetric effect for winners and losers consistent with De Bondt and Thaler (1985), Da Costa and Newton (1994), Dissanaike (1997) and many others. Having observed that losers are much smaller firms compared to winners (in terms of prices and market values), they estimate pooled cross-sectional and time-series regressions of Holding Period Returns (HPR) on price, size, and on both price and size. They discover that for the US, Canada, and Japan price is significant, and size is insignificant, while for Japan, both factors are significant and negative. Results, which are similar for the UK, indicate the possibility of prices explaining results (since falling prices mean rising HPR). However, results for the rest of the countries are not easily categorised, in some cases they are explained by size, in others by price.

However, Da Costa and Newton (1994) show that the low-priced firm effect does not explain predictability and contrarian profits. This is also the case for Bowman and Iverson (1998), who divide their sample into firms priced less and more than a US dollar, to find that the two samples exhibit no difference in their behaviour. In addition, Ball et al. (1995) also state that the low-priced firm effect only explains a portion of results.

2.7.2.6. Investor's preferences proposed explanation

Daniel and Titman (1997) are interested in an explanation for the performance of strategies based on size and book-to-market ratios (B/M). They test several propositions, and end up with the idea that value characteristics are responsible for the value premium and not risk, e.g. investors prefer growth stocks and not value stocks, which results to low price, and high expected returns for value stocks. NYSE, AMEX, and NASDAQ data for the period between 1968 and 1993 are used to test three models. The first model is consistent with Fama and French's (1994) and (1996) risk premium proposal, while the second considers an unchanged factor structure, but with varying return premium. According to the third model, firm characteristics and not risk are responsible for profits. The empirical results are inconsistent with the first two models (factor pricing models), and consistent with the third one (firm characteristics model). The results are also consistent with Fama and French (1992) who propose that the relationship between beta and returns ceases to exist post 1963. Even after controlling for size, high B/M firms outperform low ones by more than 0.5% per month for all but the largest firms, which are found to have lower returns than medium and smaller firms. In addition, they observe that January affects large firm returns, with all of the high B/M effect occurring in that month, while for small firms the effect is shared in and out of January.

The possible explanations considered for their results are behavioural, i.e. investors extrapolate past performance (Lakonishok, Shleifer & Vishny 1994). An agency explanation, i.e. agents properly assess past performance (Lakonishok, Shleifer & Vishny 1992), but act according to their preferences and not past performance. Another explanation is that these firms are undervalued because of investor beliefs that size and B/M ratio are risk proxies.

2.7.2.7. Evidence against the investor's preferences explanation

For the book-to-market and other ratios' predictive ability there have been other explanations considered apart for the overreaction hypothesis and the suggestion of Daniel and Titman (1997) above, that value characteristics are responsible for the value premium and not risk. These explanations are that it is a chance result that can occur only in specific samples and not in general (Black 1993); or that it is connected with risk (Fama and French 1993, 1996), which seems logical and consistent with the EMH.

Davis, Fama and French (2000) test this proposition related to the value premium in the paper just reviewed. They employ NYSE data from Moody's industrial manuals in conjunction with COMPUSTAT data for NYSE, AMEX, and NASDAQ for the period 1925 to 1996. The paper uses the three-factor model of Fama and French (1993) for regression analysis. The results indicate that like all models, the three-factor model is itself only an incorrect representation of reality, but quite a good one. They show that the explanation proposed by Daniel and Titman (1997) is confined to their sample period. They find that the value premium is robust for both sub periods used in the study (namely 1929-1963, 1963-1997), and that the size effect has smaller power than it has for returns. In any case, the important part of this study is that it disproves the preferences suggestion, which is competitive to the overreaction hypothesis when using accounting ratios such as book-to-market ratios.

2.7.3. Behavioural models' proposed explanation

The thesis literature review now moves in a different area that considers both efficient and inefficient markets, and focuses more in human psychology. Barberis, Shleifer & Vishny (1997), based on Tversky and Kahneman (1974), propose a psychological model consistent with both overreaction and underreaction. More specifically, they consider the psychological notions of the representativeness heuristic related to overreaction, and the conservatism heuristic related to underreaction. According to their model, arbitrage cannot eliminate short-run price diversions from equilibrium, and although in reality earnings follow a random walk, investors[53] believe that they don't, and expect two regimes: under "regime 1" earnings are mean reverting and under "regime 2" earnings follow a trend. In the first case positive news are likely to be reversed, in the second they are to be followed by more positive news. When the investor observes an earnings announcement followed by another of the same sign, he assumes that the 2^{nd} regime holds, when the opposite happens, then he assumes that the 1^{st} regime holds. For underreaction, the agent must believe in regime 2. If the shock is positive then returns will be small since they agree with expectations, but if the shock is negative, then the surprise will be large and returns will be large and positive.

On the empirical side, the~~y~~ authors run simulations for 10,000 price observations. They calculate mean realised returns for one, two, three and four positive shocks followed by one, two, three, and four negative ones respectively (each shock a year apart). They observe short-run underreaction and longer-run overreaction consistent with the literature so far. Then, they use past prices for sorting instead of previous returns, but results are similar. Finally they test for the predictive ability of accounting ratios, using the E/P ratio, calculating the difference in mean returns between higher and lower than average E/P periods, using many different periods. They find positive results consistent with previous studies. Overall, the results are consistent with contrarian strategies supporting both overreaction and underreaction.

[53] There is one investor whose forecasts are consensus forecasts, and one asset.

Amir & Ganzach (1998) take the use of psychology a step further by proposing a psychological model that simultaneously allows for both overreaction & underreaction, by looking in the synchronous influence of heuristics such us representativeness, anchoring and adjustment, and leniency[54]. They name the difference of a forecast with the previous one "forecast revision", and the difference of the forecast and previous earnings "forecast change". They test three hypotheses using 1976 to 1990 data adjusted for splits and dividends, excluding outliers, employing both a parametric and a non-parametric approach each time. The hypotheses are: H_1: greater underreaction (anchoring) will be observed with forecast revisions, compared to forecast changes. H_2: there will be more underreaction for negative forecast modifications compared to positive. H_3: overreaction, underreaction and optimism increase as time increases. The non-parametric approach[55] reveals underreaction to new information. The parametric approach however, delivers evidence consistent with both underreaction and optimism, consistent with the third hypothesis. Then they separate the effect of each type of forecast revision, obtaining results that are supportive of hypothesis two, given that β's are positive (negative) for positive (negative) forecasts revisions. In addition, analysts are more optimistic making negative revisions compared to positive.

They next focus on the 1st post announcements month. Non-parametric analysis results are consistent with the overreaction hypothesis, while parametric test results are consistent with both overreaction and optimism. Separating again

[54] Representativeness leads to overreaction. Anchoring and adjustment lead to underreaction. Leniency leads to optimism, that is, overreaction (underreaction) to good (bad) news.

[55] This just observes the relationship of negative and positive forecast revisions with forecast errors.

between negative and positive forecast changes, they find asymmetric overreaction (underreaction) for positive (negative) forecast changes, consistent with the second hypothesis. Finally, they focus in 2, 3, and 10-month periods and find positive results for optimism and overreaction consistent with H_3. When separating the effect of negative and positive changes, results are consistent with H_2, and even when controlling for measurement errors they do not change showing over- (under) reaction to forecast changes (revisions). In addition, over- (under) reaction is observed for positive (negative) forecast changes (optimism), and the longer the horizon, the higher the effect. Findings give a reasonable explanation for the conflicting previous studies results that argue whether overreaction or underreaction predicts the future. The paper takes literature forward, responding to the supposition of previous authors for the contrasting findings, leading us to the analysis of Easterwood and Nutt next.

Based on the above suggestions, Easterwood & Nutt (1999) use forecast inefficiency[56] to test underreaction, overreaction, and a third possibility of analysts being systematically optimistic. According to them, analysts underreact to bad news and overreact to good ones, since they produce forecasts that induce stock trading (Womack 1996). They use a sample of 10,694 firm-annual observations, excluding outliers, and they first replicate Abarbanell and Bernard's (1992) work, finding similar results. Nonetheless, because results can be interpreted both as systematic underreaction, or underreaction to bad news; they modify the tests to separate for the effect of the above possibilities, by grouping firms in low, medium, and high performance teams. Then they

[56] Biased forecasts, unable to incorporate new information leading to temporary miss pricing.

propose two models: a model about predicted earnings change as a function of the prior year's performance, and a model about actual current earnings change as a function of prior annual performance. Results show that analysts are systematically optimistic. They next focus on the previous year's forecast errors instead of unexpected earnings in order to address analysts' reaction to earnings, returns, macroeconomic or industry specific factors, and other events. Estimating again three models, they obtain similar results as before for high and low past earning cases. They also find that the performance of medium firms does not have any specific implications for next year's earnings. The paper's results are consistent with both overreaction and underreaction, and it's models really build on the work of Amir and Ganzach (1998).

Daniel, Hirshleifer & Subrahmanyam (1998) search for an explanation for stock miss pricing based on psychological explanations to extend De Bondt & Thaler's (1995) work. Their theory is based on investor overconfidence and changes in confidence levels due to biased self-attributions. More specifically, an overconfident individual overreacts to private information and underreacts to public information, correcting price slowly. Put simply, the proposed theory suggests that investors are overconfident, underestimating their forecast error, believing they have better forecast ability than they really do. This confidence increases (falls) when public information agrees (disagrees) with their forecasts.

They propose two models; one with a static confidence variable, which when extended leads to the changing confidence model. They run 50,000 simulations and find that when public news agrees with investor's beliefs, there is an initial price increase (further overreaction) and then decrease (progressive correction), with positive (negative) short-term (long term) autocorrelations. In addition, when considering accounting information as noisy public information, they find a positive relationship between accounting ratios and price on the short run, due to continuing overreaction, and a negative long-run relationship. Investors appear to overreact again to private news and underreact to public news (but public news initially creates further overreaction when agreeing with private information). This study is the first to change the long belief that positive return autocorrelations are due to underreaction, and negative due to overreaction. It explains that post-announcement drift can be due to overreaction as well as to underreaction. Not only that, but it also appears to explain the ability of prise based measures (B/M, E/P, dividends, market value etc) to describe returns with psychological reasoning. The study's theory is in line with both over- and underreaction and acts as the missing link between them, explaining why most previous papers find short run positive & long run negative autocorrelations.

Hong and Stein (1999) work in the same direction as Daniel et al. above, and Barberis et al. (1998), but they do not focus on one agent but on interaction between different types of agents. They also follow the work of De Long et al. (1990) and Cutler et al. (1990). Their model proposes two different investor types, "newswatchers", and "momentum traders" that have limited rationality and are able to process only part of the public information. Newswatchers make forecasts using private information while momentum traders use past prices. When only newswatchers are at work, prices adjust gradually to information and there is only underreaction. If momentum traders come in the scene, they take advantage of this and trade on it several times making a profit until asset prices revert. This happens because some traders change from momentum to contrarian traders. According to the model, the smaller the momentum trader's horizon is, the sooner price reversals will occur. As the momentum trader's risk tolerance increases, the higher the final overshooting distance will become, leading to less underreaction and a magnification of the overreaction to come at the same time. The addition of contrarians in the model is consistent with the expectation of initial underreaction leading to long-run overreaction. Firm size is important in the model, and the smaller the firm is, the slower news for it goes about, and the fewer ~~are the~~ analysts that follow them. The same procedure is considered to hold for both public and private news, but with different initial responses and stronger reversion for private news. In simple words the smaller the firm in question, the stronger will be the short-run positive correlation and the long run negative serial correlation of prices. The less public the information, the stronger the future overreaction will be; and the longer the momentum traders' horizon, the later and stronger the overreaction will occur.

Hong, Lim, and Stein (2000) test the model proposed in the above study using Jegadeesh and Titman's (1993) method earlier analysed. They test for size and analysts coverage as proxies for slower information diffusion using NYSE, AMEX, and NASDAQ stocks between 1976-1996. Results indicate more than 0.5% of momentum profits per month. Nevertheless, momentum has a negative outcome for smallest stocks (considered to be explained by slower information diffusion), and a positive one that peaks in the third size-group. They also observe an asymmetry, according to which losers are responsible for most of the momentum effect and not winners. They then create three subsamples based on residual analysts' coverage excluding the bottom 20th percentile of firms for 1980 to 1996. Portfolios are formed based on the past six-months raw-returns and are held for six months. Consistent with theory produced by Hong and Stein (1999) the momentum effect is higher for stocks with low residual coverage, and losers drive results on extreme portfolios. Based on results, they propose that analyst coverage is important when it comes to bad news that firm managers are not very keen on revealing. Thus, when firms are smaller and with low analysts coverage bad news will take more to be incorporated in prices and a drift will be observed.

Analysing findings by four size groups, they observe that moving from smaller to larger firms the momentum effect approaches zero for the largest firms. Using market-adjusted returns, raw returns, controlling for bid-ask biases and January, do not change results, which hold even when braking up the testing periods (results hold well for the first two 1980-1984, 1895-1990, and indicate lower momentum for the last period 1991-1996). Focusing on event time beta-adjusted returns, low-coverage stocks underreact by 20% compared to high coverage stocks that underreact by 9%. The results are similar even when they attempt a regression excluding stocks belonging in the smallest 20%, and those with incomplete data for period t+5. They find negative effects on correlation produced by analysts coverage, or in other words the less the analysts coverage is, the higher the momentum effect. Similar, but statistically insignificant results are obtained for size. The results are consistent with the theoretical model proposed by Hong and Stein (1999), since the stocks for which information gets out more slowly exhibit higher momentum, agreeing with their notion of a gradual information flow momentum. The paper is considered to complete the previous paper, taking behavioural models even further.

Doukas and McKnight (2003) also test the propositions of Hong and Stein (1999) on gradual dissemination of firm specific news, as well as Barberis et. al (1998) on investors' conservatism. The use I/B/E/S and Datastream data on on analysts forecasts and 3,084 firms of 13 European stock markets for the period between 1988 and 2001. Their results are consistent with short–term momentum, and also support the findings of Hong et al. (analysed just above), that both size and low analyst coverage affect the profitability of momentum strategies. Consistent with Barberis et al (1998) investors exhibit conservatism (or anchoring) and fail to properly weight new information, underreacting and leading prices to adjust with a drift that causes momentum. The momentum is significant for 8 out of the 13 Markets employed in the study.

Aiyagari and Gertler (1999) move away from previous papers by creating a model that explains overreaction of asset prices based on short-term interest rates, dividends and supply of assets. They propose that traders lever them selves by borrowing directly from unspecialised public, or by engaging in futures and options transactions. In either case, they assume that traders face margin requirements, which affect the behaviour of these risk averse individuals. As they come close to violating their constraints, due to some shock that drives asset prices down, they have to liquidate their positions, which leads to a short-term overshooting of the liquidated assets' prices, or, in other words to an initial overreaction of traders. The effect can take place not only due to facts, but also due to anticipation or the possibility of such a fact occurring[57].

They further believe that arbitrage is only possible for a small group of specialists, and that even specialists find it hard to obtain finance and take advantage of arbitrage opportunities in the very short-run. Thus, the overall result is that asset prices can temporarily overreact and depart from their equilibrium levels. On the longer run, traders take advantage of the existing arbitrage profits opportunities, and prices return to equilibrium. They run statistical analysis and simulations, which show that there could be an overreaction due to a permanent rise in the discount rate, or a permanent cut in the dividends, or an increase in asset supply. The margin constraints that traders face, play a key role in the results, but traders in real life do not maintain leveraged positions all the time, and the model cannot constantly explain reality under all economic situation and states.

2.8 Conclusion

Current literature agrees that the random-walk model does not describe asset returns, and that future returns can be predicted using past information and only that. A number of strategies attempt to exploit this finding, and one of these is the contrarian strategy that sells short past winners to buy past losers expecting price reversals in the future, and thus profits. With regards to methodology, some are long-run strategies (De Bondt & Thaler 1985, Chopra and Lakonishok

[57] As an example a rise in short-term rates and expectations, has made bondholders in the past to liquidate part of their assets to avoid margin calls, leading to a magnification of the price drops.

1992), other are short-run ones (Lehmann 1990). Some strategies refer to individual stocks, stock portfolios, national or international indices (Richards 1997), while others use parametric, non-parametric, or even both approaches for their tests, and construct their portfolios based on past returns (Pettengill & Bradford 1990), accounting ratios (Lakonishok et al. 1994, Dreman & Berry 1995), size (Zarowin 1990) etc. Other studies use equal-weighted portfolios and indices and others value-weighted ones, and so on.

No matter the method used, most of the studies find positive evidence for contrarian strategies, there is a disagreement however on the reason behind the results. Some propose *overreaction* (e.g. Pettengill & Jordan 1990, De Bondt & Thaler 1985, 1987, Lehman 1988), according to which investors are overly optimistic (pessimistic) for stocks that have done well (badly) in the past, and drive prices away from equilibrium temporarily. When more news enters the market, investors revise their expectations and thus prices revert to fundamental values, turning winners in to losers and vice versa. Others propose *underreaction* (Mendenhall 1991, Abarbanell & Bernard 1992) where stock prices adjust to new information with a drift, or even a combination of the first two like Dreman & Berry (1995). Chopra, Lakonishok & Ritter (1992) consider *seasonal effects*, while Zarowin (1990), and Clare & Thomas (1995) propose *size effects* to be behind results. Others like Lo & Mackinlay (1990), Chordia, and Swaminathan (2000) consider *lead-lag explanations*, in an inefficient market context. Some propose *risk* (Chan 1988, Ball & Kothari 1989) or *microstructure biases* (Kaul & Nimalendran 1990, Kaul, Conrad, & Gultekin 1997) to explain results in an efficient market context, while others believe that investors and/or analysts *behavioural aspects* are behind results (Barberis, Shleifer, and Vishny 1997, Amir & Ganzach 1998).

Most studies agree that:

1) Contrarian strategies deliver profits with a lag, or in other words, there is an initial momentum prior to the return reversals. For example: Chopra et al. (1992) find a year's lag and Lehman (1990) talks about a weeks lag using weekly data, when at the same time Pettengill & Bradford (1990) find a lag of the six months using daily data. Jegadeesh & Titman (1993) show that for the first eight months relative strength strategies work, but after that contrarian strategies work.

2) In many cases, overreaction is asymmetric for losers and winners; also the more a stock loses in the previous period, the more it gains later. For example, Ball Kothari and Shanken (1995), and Dissanaike (1997) results indicate that return reversals are higher (or only) for past losers but not for winners, thus the overreaction hypothesis seems for them half true.

3) There is a January effect, where a lot of the abnormal returns come from, but the overreaction phenomenon is other than the January effect, for example: De Bondt & Thaler (1985,1987) find most of the returns to occur in January, while Jegadeesh (1990) finds abnormal returns of 4.37% in January and 2.2% out of the month of January. In addition, Pettengill & Bradford (1990) find two-thirds of abnormal returns in Januarys. In all cases

however, the authors make it clear that the predictability is not confined to the month of January.

4) There is a size effect, in the sense that small firms experience larger abnormal returns, but the overreaction phenomenon is other than the size effect, for example: De Bondt & Thaler (1985, 1987) find a small firm effect only in January. Pettengill & Bradford (1990) show that the smaller the firm the larger the abnormal returns, while Chopra & Lakonishok (1992) actually discover that small firms have 7.9% abnormal returns, when medium and larger ones have 3.5% and 2.6% respectively.

A few of the figures on the magnitude of profits are now presented in order to quantify them, for example: De Bondt & Thaler (1985) find contrarian profits equal to 24.6% per three years period. Jegadeesh (1990) shows losers that outperform winners by 34.3% per annum, 1.99% per month, and 0.93% per month, depending on the strategy applied, while the strategy of Pettengill & Bradford (1990) delivers excess returns of 14% per annum for extreme portfolios. Chopra Lakonishok and Ritter (1992) find 6.5% excess returns for contrarian portfolios that become 2.5% after controlling for risk, and 4.9% when using a multifactor model. As has been seen in other studies, arbitrage contrarian profits remain significant even when taking in to account for reasonable transaction costs.

The main question after reviewing all this literature remains the same, and is related to whether there are genuine abnormal returns or just compensation for bearing excess amounts of risk, in which case markets would be efficient. If there are however abnormal returns not related to risk, the question is whether they are due to human error, data mining, bid-ask bias, thin-trading etc, under an efficient market again. If however none of the above gives a convincing and stable over time answer, then one could conclude that there might be an anomaly at work, such as overreaction and/or underreaction, size effects, low priced firm effects, January effects. All these need to be considered before one comes in to solid conclusions about return predictability and contrarian strategies.

The literature review has shown that no explanation is convincing persistently, and our personal view is that the truth lies some where in the middle. Size and seasonality might affect results, with smaller less followed firms making most of the profits in January, but these two anomalies do not explain a large enough portion of results. Bid-ask biases and thin trading can also affect results; but can be avoided by applying simple methods. Risk, the way it is perceived, explains only a small portion of results in most cases, either because part of the profits are risk free, or because there are other unconsidered sources of risk. Furthermore, when using a model to describe returns with a proxy factor for the market portfolio one must be careful in interpreting results. This is because, results might not actually be testing for market efficiency or overreaction, but for how good the model is in describing asset returns, or how close the proxy used is to the theoretical real market index of all risky assets. Put simply, results might only be due to the joint hypothesis problem. Finally, the thesis supports the idea that both overreaction and underreaction can simultaneously act as logical predictability explanations, since human agents are involved with different psychologies that affect their behaviour, while information asymmetries are present. Although theoretical behavioural-based explanations are interesting, they are a puzzling solution with large grey areas that might last for a long time.

As a next step, the Greek Market that is the main focus of the current thesis is briefly described in order for the reader to grasp the basic characteristics of this specific stock market, its importance for the Greek economy, and how the market has evolved over time.

CHAPTER III.

THE ATHENS STOCK EXCHANGE

3.1 Introduction

The objective of this chapter is to provide the reader with an overview of the Hellenic market that monopolises the interest of this thesis. The need for this, stems from the fact that this is not a major market, and therefore information about it is not widespread; this becomes more important given various unique characteristics for which emerging markets are renowned.

The only Greek stock exchange is the Athens Stock Exchange (ASE) that was established in 1876 as a self regulated public institution. The most important part however of its long history is related to the last 15 years, when public demand and European Union directives[58] resulted to numerous changes that modernized the market and enhanced its transparency. For example, in 1988, law 1806 introduces the parallel market and the Central Securities Depository. The Parallel Market is for smaller firms that cannot meet the criteria for entering in the main Market. In addition, in 1990, law 1892 establishes the Central Securities Depository as a joint stock company, and a year later, the Capital Markets Commission is established as a supervisory authority by law 1969; the same law regulates the foundation of Portfolio Investment Companies and mutual funds. In 1995, the ASE is transformed into a Joint stock company by law 2324, while the same law allows over the counter transactions[59], short selling, and deregulates commissions among

[58] For the most important early European Union Directives see Appendix 3.5.1

[59] Over The Counter (OTC) transactions on listed shares can only be performed during trading hours with the concession of the issuer, provided that the member firm guarantees the OTC trade for at least 1 year. OTC transactions cannot be performed on stocks for which the ratio (Highest annual

other things. In 1997, the legal framework for the ASE privatisation is introduced by law 2533, which also establishes the derivatives market (ADEX) together with the parallel market for emerging markets and the fixed income securities market. The ADEX product range includes futures based on the FTSE-ASE 20 and FTSE-ASE 40 Indices and on the 10-year Greek government bond.

The ASE is monitored by the ministry of National Economy, and is governed by an independent board of directors[60] consisting of eleven members appointed for three years. The board is responsible for the administration of the exchange, and for granting market memberships. The Minister of National Economy appoints the President of the ASE, who monitors its workings, halts trading when it negatively affects investors, and allows block trades[61]. The Capital Markets Commission is one of ASE's regulatory bodies, and it is formed of eleven members and it's president, all appointed by the Ministry of National Economy. Its primary task is to protect investors' interests and to monitor whether market participants deviate from the rules.

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price-Lowest annual price)/Average annual price, exceeds by more than 50% the corresponding ratio of the ASE. General Price Index and by 20% the corresponding ratio of the share prices of the same sector. OTC trading stops within 6 months after such deviation is observed [source: ASE " Fact Book 1998").

[60] See Appendix 3.5.2 for the composition of the board of directors

[61] Block trades are trades of a value greater than or equal to 100 million GRD (now increased to 200 million). Block trades can be affected outside the Automated Exchange Trade System, provided there are no opposite bids or offers, within the system, in values equal to or greater than the value of the respective transaction. A block of shares may be transferred with a 5% price difference in either direction from its current market value, when the total value of the block amounts to GRD 200-400 million. In trades over GRD 400 million, the price can be formulated with a 10% difference in either direction from their last transaction price or from their closing price. (ASE " Fact Book 1998")

Investor protection is ensured by the daily surveillance of transactions from the Ministry of National Economy, and the fact that ASE member firms are not allowed to trade without the consent of their customers. By decision of the Capital Markets Commission, the value of all daily trades conducted by the members of the ASE that exceeds the value of their net equity, must be covered by bank guarantees, additional capital, or the shares themselves. When the value of the total daily trades exceeds by two times the net equity of the member firm, and no additional guarantees are provided, access to the electronic trading system is refused to that member firm (source: ASE "Fact Book 1998"). Another way to protect investors from large price fluctuations is a price limit set from the authorities in daily trading. This limit is set to 12% price movement in any direction (except for the first three trading days of IPO's). Some support however, that this measure reduces trading volumes and market efficiency by reducing the speed of adjustment to information.

Today the Athens Stock Exchange is owned by Hellenic Exchanges S.A. 40.9% of which is controlled by the Greek Government, 26.4% by Banks, 14.9% by Institutional Investors, 9.9% by investment public, 5.2% by Listed companies, and 2.7% by ASE Members.

The chapter proceeds as follows: section 3.2 describes the trading procedures of the ASE, while section 3.3 presents market statistics. Section 3.4 concludes the chapter and section 3.5 is the Appendix to the chapter.

3.2 Trading Procedures

The Athens Stock Exchange trades Monday to Friday between 11:00 a.m. and 4:00 p.m. (9:00-14:00 GMT) with a half hour pre-opening period and a fifteen minutes post-closing period. For a brokerage firm to trade in the exchange, the Board of Directors must approve it. All transactions are in cash, and they are performed on the exchange.

Trades are regulated by the ASE and conducted electronically through the Integrated Automated Exchange Trade System (OASIS). Orders are entered into the system by stock exchange representatives, who are supplied with code numbers for that purpose. Orders are entered either from the floor of the exchange or from the offices of the members, by means of remote broking operations. Each member-brokerage firm is allowed up to eight terminals, the use of which is restricted to the trading hours of the stock exchange (source: ASE "Fact Book 2001").

All orders introduced into the system before 10.00 a.m. can participate in the formation of the opening price. At the pre-opening period, the system accepts limit and market orders. Limit orders determine the day's opening price, while market orders get time priority for execution soon after the opening of the market. If no limit orders exist, the opening price will be the same as the previous closing price. The criterion used for the determination of the opening price is the maximization of transactions' volume. When two prices produce the same maximum volume, the price closest to the previous closing price is selected. If their differential from the previous close coincides, the system will select the highest price of the two. Closing prices are formulated as the weighted average of the execution prices of the transactions of the last ten minutes of the day. If no orders exist for that period, then the last twenty or thirty minutes weighted average is considered, and if there are no transactions for this period as well, then the closing price is a weighted average of all of the day's transactions (source: ASE "Fact Book 2001"). So they are not bid, nor ask prices but an average of transaction prices, and thus there is no case of bid ask bias (we return to this later in the chapter, and chapter 5 as well).

At the main trading session, orders are matched by price (the buy order at the highest price is matched with the sell order at the lowest price) and time. The computerized system is capable of handling 200,000 orders per hour. Members can change or reverse their orders during the main trading session if they feel that their orders cannot be executed under the given price. *During each trading session, the* trading system forms a central book of pending round lot orders. These are separated to buy and sell orders and are ranked by price and given time priority. There is also a secondary book of pending orders. All new orders are automatically checked (depending on share quantity) against orders listed in the main board and the odd lot book (source: ASE "Fact Book 2001").

Trades are continuously confirmed by printouts, stating the exact order, the price of the transaction, the precise time of the trade, the volume and the code number of the counterpart. Once an order is executed, the transaction is confirmed between the participating parties and is copied from the "scratch pad" to the transactions list. The list displays the time at which the transaction was executed as well as the code numbers of both the customer and the participating broker, ensuring full market transparency (source: ASE "Fact Book 2001").

Types of orders handled by the system are: *Open price orders* (if the counterpart cannot fully cover the order, then it is partially executed, and the system cancels the rest of the order). *Market orders* (if the counterpart cannot fully cover the order, then it is partially executed, and the rest of the order becomes a limit order). *Limit orders* that can be partially executed with the non-executed portion of the order queuing on the system for execution at the price limit. Investors can also set time limits for the order to be executed. *Stop orders that* are only activated when a specific criterion is satisfied. *Immediate or cancel orders* that are cancelled if not carried out immediately. *Odd lot orders,* which are introduced in amounts smaller to the lot unit of each share; they are executed at the market prevailing price (source: ASE "Fact Book 2001").

Over the counter trades are allowed under specific conditions (see footnote 59). Repurchase agreements are also allowed under certain conditions, while trading out of hours is not allowed. Trading fees are set at 0.02%, and commissions are deregulated since 1995 and set freely from trading parties (source: ASE "Fact Book 2001"). For information on taxes, see Appendix section 3.5.3.

3.3 ASE Statistics

During much of the 1980s Greece applied a set of heavy restrictions on capital and foreign exchange markets. This made it very difficult for international investors to access local markets. However, following the adoption of European Community legislation that aimed at deregulating member states' capital markets, a wave of financial market deregulation occurred during the late 1980s and early 1990s. For much of this period, the Greek financial system was still characterized by a strong commercial banking sector that dominated equity markets. As a result, local firms, which were often characterized by family ownership, traditionally turned to banks for capital, despite the fact that an organized equity market, the Athens Stock Exchange, has been functioning for almost 125 years.

More recently, this has changed with business increasingly turning to the equity market for capital. For example, as can be seen from Table 3.1, the number of listed companies in the ASE more than doubled in the 1990s: listed firms grew from 145 in 1990 to 342 in 2000[62]. Similarly, market capitalization increased from 12,023.6 million Euros in 1990 to 117,956.2 million Euros in 2000. See also figure 3.1 for the total Market capitalization broken down in sectors. A similar pattern can be observed for average daily trading volume that increased significantly from 12.9 million Euros in 1990 to 407.7 million Euros in 2000. Equity market capitalization as a percentage on nominal GDP rose from 20% in 1995 to well above 100% in 2000. Note the significant increase in trading volumes and market capitalization for

[62] See also figure 3.2

the years 1999-2000 when the expectations of Greece joining the Euro-zone, falling inflation and interest rates, and the large number of public infrastructure projects that were announced for the 2004 Olympic Games led a prolonged rally in equity prices in the ASE. During this period, local individual investors (many of whom abstained from the market until then) along with an increased demand for equity holdings from abroad, lead to average daily trading volumes of 723.8 million Euros (around four times the volume of 1998).

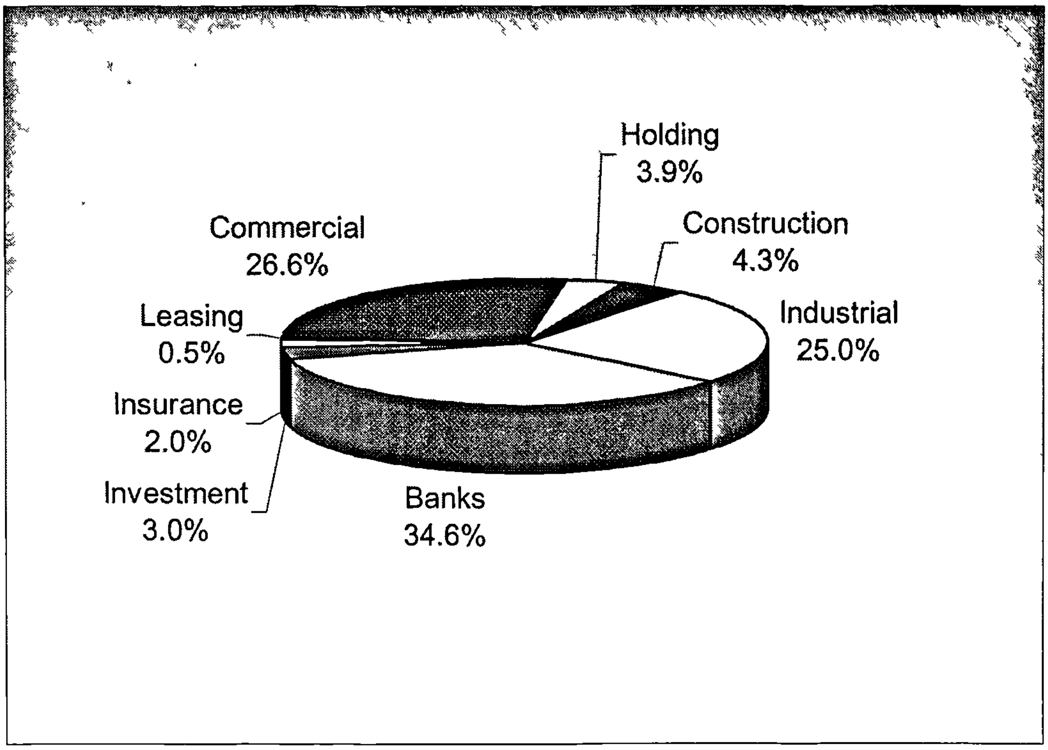
Local firms were fast to capitalize on that increased demand and rushed to strengthen their capital base and raise capital: as can be seen from Table 3.2 and figures 3.3 and 3.4, there were 175 capital raises during that period to the level of 8,064.8 million Euros. Given the growth and changes experienced by the ASE, this is a good test case to analyze the sources of contrarian profits, if any at all.

Table 3.1
Descriptive Statistics (Athens Stock Exchange)

Year	Average Daily Trading Volume	Total Market Capitalisation	Number of Listed firms
1990	12.9	12,023.6	145
1991	8.0	10,450.8	159
1992	4.9	8,283.3	164
1993	9.3	11,624.5	150
1994	17.4	12,453.6	196
1995	18.7	13,440.3	215
1996	26.5	19,720.7	235
1997	75.9	31,806.3	237
1998	169.2	68,882.5	258
1999	723.8	206,601.3	294
2000	407.7	117,956.2	342

Source: Athens Stock Exchange, Marketing Department, in million of Euros.

Figure 3.1
Market capitalization 2000 (Athens Stock Exchange, % of Main Market)



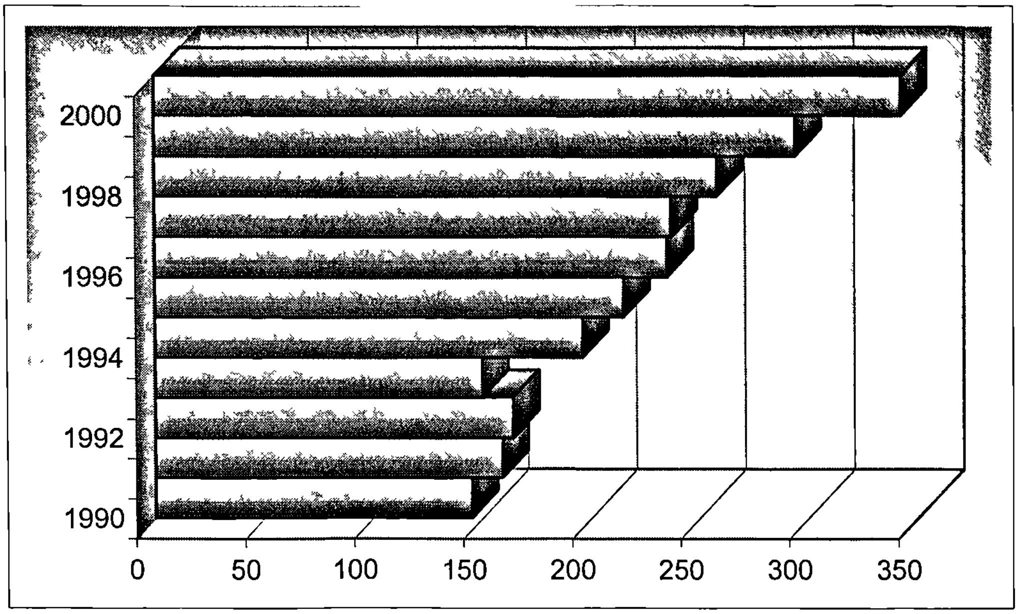
Data Source: ASE "Fact Book 2001"

Table 3.2
Capital Raised in the Athens Stock Exchange (1998-2001)

	Number of Firms Raising Capital	Capital Raised
1998	4	99.791
1999	31	2,676.7
2000	103	4,948.36
2001	17	340.000
Total	175	8,064.852

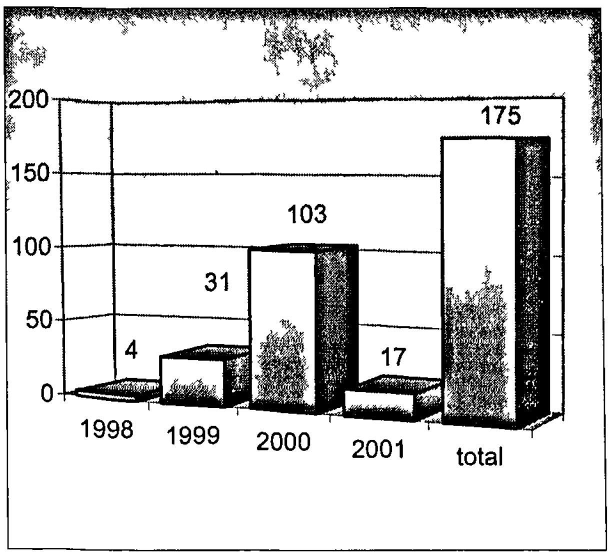
Source: Athens Stock Exchange, Marketing Department, in million of Euros.

Figure 3.2
Number of listed firms (Athens Stock Exchange)



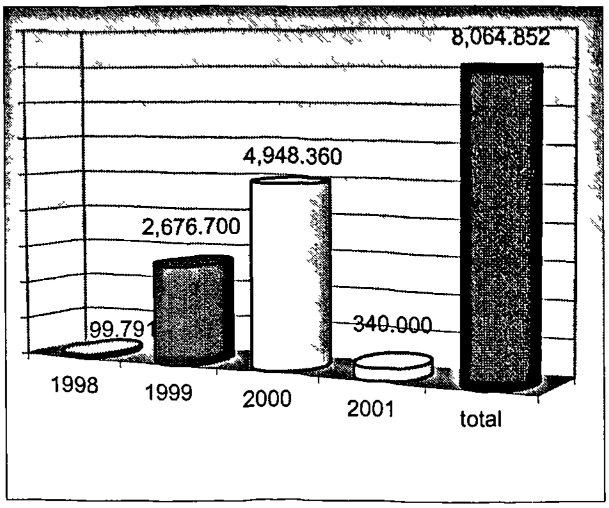
Data Source: ASE "Fact Book 2001"

Figure 3.3
Number of firms raising capital (Athens Stock Exchange)



Data Source: ASE "Fact Book 2001"

Figure 3.4
Capital raised (Athens Stock Exchange, in million Euro)



Data Source: ASE "Fact Book 2001"

Table 3.3, depicts the behaviour of ASE indices for the period between 1990-2000 (The most important indices are the ASE GPI, the Parallel market Index introduced in August 1995, the FTSE ASE 20 Index introduced by ASE & the Financial Times in September 1997, and the FTSE-ASE MID 40 introduced two years later). As can be seen on average growth is steady for all sectors and the GPI until 1998, and then there is a rally during 1999 amid bullish investor sentiment and the feeling that Greece is very close to qualifying for the EMU. As a result, all indices double at least, the ASE GPI increases by 102% reaching an all time high in September (6,484.38 units), construction companies prices increase by 586%, and the best performer is the parallel market gaining 658%; while at the other end the FTSE /ASE 20 index increases by less than double. During 2000, prices decrease but are still at higher levels compared to their pre-rally magnitudes. Nowadays however they trade in most cases at lower levels than 1998.

Table 3.3
Share Price Indices (Closing Prices)

Year	Banks	Insurance Companies	Investment Companies	Leasing Companies	Industrial Companies	Construction Companies
1990	1,073.56	823.60	661.05	279.13	701.65	
1991	1,010.71	777.54	453.94	321.31	539.41	
1992	809.48	619.41	312.60	346.02	493.15	
1993	1,005.07	805.09	420.80	397.02	826.21	
1994	1,034.58	501.74	361.96	318.14	709.39	704.25
1995	1,160.29	315.20	325.75	295.77	743.29	675.49
1996	1,413.81	314.77	335.00	227.55	717.40	412.97
1997	2,303.30	734.95	597.33	259.28	1,167.28	445.97
1998	5,799.42	1,290.89	876.48	343.02	1,714.03	502.15
1999	10,165.41	3,731.09	2,822.70	1,545.55	3,451.61	3,446.01
2000	7,306.98	1,383.92	1,335.07	545.60	2,072.80	1,271.88

Year	Holding Companies	Parallel Market	FTSE/ASE 20	FTSE/ASE MID 40	ASE index Composite	All Share Index
1990	-	-	-	-	932.00	313.64
1991	-	-	-	-	809.71	270.04
1992	-	-	-	-	672.31	233.20
1993	-	-	-	-	958.66	339.07
1994	557.81	100.00	-	-	868.91	326.54
1995	707.04	107.38	-	-	914.15	344.50
1996	677.27	71.40	-	-	933.48	346.03
1997	1,291.76	77.53	845.88	-	1,479.63	516.67
1998	2,155.99	208.66	1,724.24	-	2,737.55	1,049.29
1999	6,770.43	1,582.58	2,910.10	1,000.95	5,535.09	2,755.05
2000	3,851.29	319.72	1,950.95	395.44	3,388.86	1,950.95

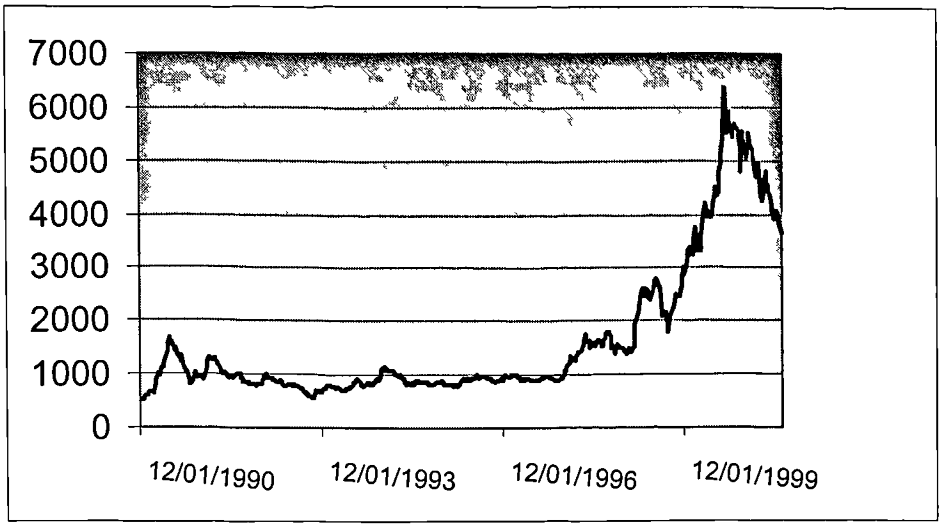
Notes to table 3.3:

All Share Index Base: 04.01.1988 = 100 Units, Parallel Index Base: 31.12.1994 = 100 Units, Leasing Companies Index Base: 31.12.1987 = 100 Units, FTSE/ASE 20 Index Base: 24.09.1997 = 1000 Units, FTSE/ASE MID 40 Index Base: 8.12.1999 = 1000 Units Other Indices' Base: 31.12.1980 = 100 Units.

The ASE General Price Index[63] is a value–weighted index that is composed of the most heavily traded stocks that represent approximately 70% of total market capitalisation and approximately 80% of total transactions volume. Figure 3.5 shows that it increases significantly from 518 units in 1990 to around 6000 during 1999 after the rally mentioned for that year, to drop back to lower levels after that. Currently (2002), the index is at a very low level of less than 2000 units.

[63] For a list of the constituents of the ASE GPI and the FTSE/ASE20 see Appendix section 3.5.4

Figure 3.5
ASE General Price Index 1990-2000



Data Source: Datastream International

3.4 Conclusion

During the late 80'es the Greek market is characterized by large organizational changes, which remove most of the constraints for foreign investors, be it political, administrative or legal. These changes enhance liquidity, information disclosure and the technical organization of the market, and facilitate the change of the Greek market from emerging to developed. Thus the market in the 90es is more open to foreign investors and thus the subject of more market scrutiny. The above make the market more interesting, and provide motivation for tests on its characteristics, under this light. In addition, the behaviour of prices varies during this period significantly: prices exhibit stability up to 1996, then they grow steadily up to 1998, and then experience a bullish period (1999) followed by sharp drop, as can be seen in figure 3.5. This provides an interesting mix and provides additional motivation for selecting the market, because it enables tests of whether losers or winners behave differently in rising markets (1990 & 1999) than in falling ones (1991 & 2000) as De Bondt & Thaler (1987), Bacmann and Dubois (1998) and others suggest. More importantly, it can be tested whether higher volatility (1998-1999) induces more profits than lower volatility (1994-1996), as suggested by the overreaction hypothesis statement that higher price extremities (gains, loses) lead to higher reversals.

3.5 Appendix

3.5.1 Important early European Union capital market directives:

The provisions of EC Directive 211/90, amending EC Directive 390/1980 on the mutual recognition of prospectuses published for pursuing a listing on the stock exchange, were adopted by Law 1969/1991.

EC Directive 345/1987, amending EC Directive 390/1980 on the mutual recognition of prospectuses published for pursuing a listing on the stock exchange, was adopted by Presidential Decree 50/1992.

EC Directive 627/1988 on the acquisition or disposal of significant holdings in listed companies, was adopted by Presidential Decree 51/1992.

EC Directive 592/1989 on insider trading, was adopted by Presidential Decree 53/1992.

EC Directive 361/1988, as amended by EC Directive 122/92 on capital movements was adopted by Presidential Decree 96/1993.

EC Directive 93/6 on the capital adequacy of investment firms and credit institutions was adopted by Law 2396/1996.

EC Directive 93/22 on the provision of investment services was adopted by Law 2396/1996

For all the legal framework with all laws, directives etc see the Hellenic Republic Capital Markets Commission web page: http://www.hcmc.gr/

3.5.2 Composition of the Board of directors (source: ASE Fact book 2001)

The composition of the Board ensures the participation of all market participants in the decision making process. In specific, members are appointed as follows:

5 members by the Minister of National Economy
1 member by the Bank of Greece
2 members by brokerage companies, members of the A.S.E.
1 member by the Athens Chamber of Commerce and Industry as representative of listed companies
1 member by the institutional investors
1 member by the employees of the Athens Stock Exchange

3.5.3 Tax system (source: http://www.greekshares.com/athensexc.asp)

A. Shares

Dividends from listed shares are taxed at a flat rate of 35% withheld at source. Investors are therefore exempted from any tax obligation. Capital gains are not taxable in Greece. Inheritance tax is imposed on assets, the ownership of which arises from death, donation or dowry of the previous owner. Movable assets, such as shares are also subject to this tax.

The tax due can be determined either by the average value of the transactions realised in the past six months before the owner's death or, if none, by the shares book value. The tax authorities in Greece reserve the right to alter the appraised value of the security, taking into account the financial results, the name and the market position of the company, as well as the size of the holding.

A tax of 0.3% is imposed on all sale transactions. Dividends from bearer shares of companies not listed on the A.S.E are taxed at a rate of 40%.

B. Portfolio Investment Companies, Mutual Funds

New tax regulation stipulates that capital gains and profits are taxed at a rate of 3%o estimated on the average net total Assets of those companies.

C. Foreign Investors

Although foreign investors do not declare income from securities in Greece, they can reclaim the tax withheld on such securities. The issuer certifies the amount of tax withheld and the investor includes this certificate in her/his annual income statement in her/his country of residence. Foreign investors are free to import capital for investment in securities and to re-export any capital gains, dividends and interest.

Furthermore, Greece has certified conventions with many countries for the avoidance of double taxation. Under these agreements direct tax is applied, in accordance with the tax system of the country whereby the investment was generated.

3.5.4 Compositions of Indices: (source: ASE "Fact Book 2000").

The Athens General Price Index Companies

1.LAMBRAKIS PRESS
2.NATIONAL BANK
3.ALFA ALFA HOLDINGS
4.COMMERCIAL BANK OF GREECE
5.ALTEC S.A.
6.CHIPITA INTERNATIONAL
7.HELLENIC PETROLEUM
8.PIRAEUS BANK
9.ALPHA BANK
10.MOTOR OIL
11.TILETYPOS
12.COSMOTE MOBILE COMMUNICATIONS
13.HELLENIC TEXTILES
14.FANCO
15.UNISISTEM
16.HELLENIC TELECOM (O.T.E.) ORG.
17.HYATT REGENCY
18.INFOQUEST
19.INTRACOM
20.LOGIC DATA INFORMATION SYSTEMS
21.AVAX S.A. CONSTRUCTION
22.MARFIN CLASSIC
23.GERMANOS IND & COMPANY
24.HERACLES GENERAL CEMENT
25.TITAN CEMENTS
26.A.E.G.E.K. CONSTRUCTION
27.AKTOR CONSTARUCTION
28.PUBLIC POWER CORPORATION
29.ATHENS WATER COMPANY
30.N.B.G. REAL ESTATE DEVELOPMENT
31.ELVAL ALUMINUM PROCESS
32.HELLENIC EXCHANGES
33.GIANNOYSIS
34.THEMELIODOMI
35.ELLINIKI TEXHNODOMI
36.ALUMINIUM OF GREECE
37.IASO S.A.
38.NAOUSSA SPINNING MILLS
39.M.E.T.K.A.
40.MAILLIS S.A.
41.MINOAN LINES
42.ATTICA ENTERPRISES HOLDINGS

43.STRINTZIS LINES
44.MYTILINEOS HOLDINGS
45.KEKROPS S.A.
46.DELTA - SINGULAR S.A.
47.PANAFON S.A.
48.EYAPS
49.PETROLA HELLAS
50.COCA COLA
51.B. VOVOS
52.PAPASTRATOS CIGARETTE
53.SIDENOR S.A.
54.VIOHALKO
55.KLONATEX GROUP OF COMPANIES
56.TECHNICAL OLYMPIC
57.EFG EUROBANK - ERGASIAS
58.HERMES.
59.OPAP
60.ATHENS MEDICAL CENTER

Stocks of the FTSE/ASE 20 Composite Share Price Index

1.EFG EUROBANK - ERGASIAS BANK
2.AGRICULTURAL BANK of GREECE
3.TITAN CEMENT COMPANY
4.ALPHA BANK
5.VIOHALCO
6.MOTOR OIL (HELLAS) CORINTH REFINERY
7.COCA COLA
8.HELLENIC PETROLEUM
9.NATIONAL BANK OF GREECE
10.COMMERCIAL BANK OF GREECE
11.ATTICA ENTERPRISES
12.ETBA BANK
13.INTRACOM
14.ELLINIKI TECHNODOMIKI
15.ALUMINIUM OF GREECE
16.ATHENS WATER CO
17.OTE HELLENIC TELECOM ORG.
18.PANAFON
19.PIRAEUS BANK
20.COSMOTE MOBILE COMMUNICATIONS

In ASE, 94% of shares are ordinary shares, while 6% are preference shares (that have a prior claim to dividends and may be voting or non-voting) and preferred ordinary shares (which are voting and carry a fixed dividend).

CHAPTER IV.

PROFITS OF LONG TERM CONTRARIAN INVESTMENT STRATEGIES UNDER RISK VARIATION AND SEASONALITY

4.1 Introduction

The documentation of negative serial correlation in stock returns over the last 35 years (Fama 1965) has acted as the basis on which the overreaction hypothesis was built. According to the overreaction hypothesis (DeBondt and Thaler 1985), investors overreact to new information driving prices out of equilibrium temporarily, until more news is released and prices revert towards their fundamental values. Intuitively, overreaction implies that price reversals can be predicted from past information, directly contradicting the EMH. The above pattern can be exploited by following a contrarian strategy that is long past losers and short past winners, earning abnormal returns once prices start reverting towards their intrinsic values, due to the negative serial correlation.

Although well-developed markets, especially the US market, have known extensive research in the relevant area, very little research has been carried out for smaller and less developed markets. Nonetheless, it is very important to compare evidence for developed markets with results from less developed ones that are considered to have larger information asymmetries given that fewer analysts follow such markets to keep them in equilibrium with their trading. In addition, many studies discuss the importance of the empirical investigation of the overreaction hypothesis and contrarian strategies with new data (see for example, Kryzanowski and Zhang 1992, Clare and Thomas 1995 etc). Furthermore, it not clear yet, as seen in the literature review, whether contrarian profits are genuine or due to misperceptions such as risk miss measurement and microstructure biases, or market anomalies such as size and seasonal effects.

The chapter endeavours to address the above gaps in the literature by applying long-run contrarian strategies to the Athens Stock Exchange (ASE hereafter) of Greece. Since this is a representative case of a small emerging market undergoing improvements (as already discussed). Furthermore, most of the market cap in Greece is owned for the period by individual investors, and thus behavioural aspects related to overreaction are meant to play a more important role in such markets. As a first step, it determines whether ASE returns can be predicted using a contrarian strategy based on De Bondt & Thaler (1985). Nonetheless, before attributing possible profits to overreaction, the chapter tries to eliminate other explanations such as risk & changes in risk (Ball and Kothari 1989, Chan 1988), seasonality (Zarowin 1990), and volatility.

This chapter contributes to the literature in several different ways. Firstly, it examines whether contrarian profits are sensitive to the definition of abnormal returns, following the suggestion of Chopra et al. (1992). Secondly, it examines whether the length of investment horizons and volatility affect contrarian profits. Thirdly, it investigates for the possible presence of well-known monthly seasonal anomalies behind results. Fourthly, it introduces an important innovation by employing the Kalman Filter algorithm -for the first time ever in contrarian strategies- in the process of risk adjusted returns estimation, allowing for time-variation in systematic risk. According to recent evidence, beta risk is not constant through time (see for example Ross 1989). Thus, all contrarian studies carried out up to now that do not incorporate this evidence in their methodology, may have reached to biased conclusions. Fifthly, it also examines following Chan (1988) whether excess returns are just compensation for risk changes between portfolio formation and holding periods. Finally, it acts as a robustness test outside the market for which the regularity was established, which is very important (Doukas and McKnight 2003). In addition to this, no evidence on contrarian strategies exist for the Athens Stock Exchange, which is an emerging stock market, and as such, would be expected to exhibit more return predictability compared to well-developed markets. More specifically, asset prices in large and well-developed markets are expected to follow a martingale process, based on which, the price of an asset x at time $t+1$ is expected to be equal to its price at time t, given the information set at time t, Z_t: $E_t(x_{t+1}|Z_t)= x_t$. This implies a 'fair game' for rates of return in such markets, i.e.: $E_t(x_{t+1}-x_t|Z_t)=0$, according to which changes in prices are unpredictable (conditional on Z_t) in which case information is fully reflected in prices and there is no chance of long-term abnormal, risk-excess returns, i.e. markets are efficient (LeRoy 1989, Barnett and Serletis 2000).

This does not hold however for smaller less developed markets, due to supply limitations, few investment funds, low volumes, infrequent trading etc. (see for example Jennergan and Korsvold 1974, Cohen 1983, Solnic 1973 etc). More specifically for the ASE the evidence is mostly against the martingale hypothesis as that is stated above, and indicate that past price movements might have an information content for the future of assets that investors may use to predict the future (Kavussanos and Dockery 2001). This evidence is also supported by Koutmos et al. (1993) who find past returns to explain current prices, and Spyrou (1998), who uses variance ratio and runs tests and rejects efficiency for the Greek market. Panas (1990) however finds positive evidence for the martingale hypothesis; this however could be due to the very small number of Stocks he uses in his study. Given the evidence against the martingale model, which lives for predictability and contrarian profits, and in combination with the extraordinary changes in the ASE mentioned at the end of the previous chapter, it is interesting to revisit the efficiency issue, from another scope, that of overreaction.

Results will have important implications not only for financial theory but for practitioners as well. For example, with respect to financial theory results may or may not support the EMH, and will act as an additional piece of evidence. With respect to practitioners, this chapter's strategies are easily applicable, and even "small" investors with limited funds can benefit from them, given their low transaction costs (only one set of transactions per annum or even per three year-periods is required). The remainder of this chapter is organized as follows: section 4.2 discusses the data and the testing methodology, while section 4.3 presents the results. Section 4.4 concludes the chapter and section 4.5 is the Appendix to the chapter.

4.2 Data and Testing Methodologies

Based on the overreaction hypothesis, past information can predict future stock performance. More specifically, stocks are expected to move in opposite directions relevant to their past (given the negative autocorrelation in individual stock returns), leading to reversals that turn losers into winners and vice versa. This chapter applies tests that assess these expectations exactly.

Weekly price observations for all stocks listed on the ASE that have at least 260 consecutive observations[64] for the period between January 1990 and August 2000 are employed. The ASE General Price Index[65] is utilized as a proxy for the market portfolio, while the 3-month Treasury Bill is used as a proxy for the risk free rate. All the data are collected from DATASTREAM. Returns are continuously compounded, defined as the first difference of the logarithmic price levels:

$$R_{it} = logP_{it} - logP_{it-1} \qquad (4.1)$$

where:

R_{it} is the return of stock i at time t, and

P_{it} is the price of stock i at time t

log is the natural logarithm

4.2.1 Contrarian profits using market adjusted returns

As a first step in the analysis, market-adjusted excess returns for all stocks are obtained, using a special case of the market model that considers the constant to be zero, and beta to be one, similar to De Bondt and Thaler (1985):

$$U_{it} = R_{it} - R_{mt} \qquad (4.2)$$

where:

U_{it} is the market-adjusted excess return of stock i at time t, and

R_{mt} are the raw returns on the market portfolio at the same time.

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[64] This is to avoid bias of the autocovariance estimates known to occur in small samples and also for comparability of results with the next empirical chapter that uses the above criterion.

Next, the market-adjusted returns for every stock that has observations for the first 52 weeks, that is between January 1990 and December 1990, are cumulated (t=-52 to 0). This is the *formation* period. The stocks are then ranked based on these cumulative abnormal returns CU_i:

$$CU_j = \sum_{t=-52}^{0} U_{it} \tag{4.3}$$

The top five performers are assigned to an equally weighted winner portfolio while the bottom five performers are assigned to an equally weighted loser portfolio. The market-adjusted returns of these portfolios are then estimated for the following 52 weeks (t=1-52), that is, between January 1991 and December 1991, which is the *testing* period. This procedure is repeated 10 times, once for every year until 2000.

$$AR_{WNt} = \frac{1}{n}\sum_{i=1}^{n} U_{iNt}$$

$$AR_{LNt} = \frac{1}{n}\sum_{i=1}^{n} U_{iNt} \tag{4.4}$$

where:

$AR_{W,N,t}$ and $AR_{L,N,t}$ are respectively the Winner and Loser portfolios' market adjusted returns for period N at time t

N is the number of testing periods, N-1,2,...,10, while

T is time, t=1,..,52 , n is the number of stocks per portfolio, n=1,2,..,5

[65] The ASE GPI is a value-weighted portfolio composed of the most heavily traded stocks that represent a large percentage of the total market capitalisation and trading volume, as described in the previous section

Next cumulative AR's for the winners and losers are obtained, define them as $CAR_{W,N,t}$, $CAR_{L,N,t}$, respectively. This results to ten winner and ten loser CAR_t.

$$CAR_{WNt} = \sum_{t=1}^{T} AR_{WNt}$$

(4.5)

$$CAR_{LNt} = \sum_{t=1}^{T} AR_{LNt}$$

To grasp how losers and winners behave on average, an average *CAR* for losers and winners is then taken for each week of the testing period, between t=1 and t=52, as follows:

$$ACAR_{W,t} = \frac{1}{N}\sum_{n=1}^{N} CAR_{W,N,t}$$

(4.6)

$$ACAR_{L,t} = \frac{1}{N}\sum_{n=1}^{N} CAR_{L,N,t}$$

Where $ACAR_{W,t}$ and $ACAR_{L,t}$ are the Winner and the Loser portfolio average *CAR's* respectively.

Under the overreaction hypothesis winner portfolios in the formation period are expected to become losers in the testing period, and vice versa, that is, for $t>0$, $ACAR_{Wt}<0$, and $ACAR_{Lt}>0$, or equivalently, $[ACAR_{Lt}-ACAR_{Wt}] > 0$.

One way to evaluate whether there is a statistically significant difference between $ACAR_{Wt}$ and $ACAR_{Lt}$ is to use the following t-statistic (De Bondt and Thaler 1985):

$$t_{1t} = \frac{(ACAR_{L,t} - ACAR_{W,t})}{\sqrt{2S_t^2 / N}} \tag{4.7}$$

Where the pooled estimate of the population variance S_t^2 in CAR_t, is:

$$S_t^2 = \frac{\sum_{n=1}^{N}(CAR_{W,i,t} - ACAR_{W,t})^2 + \sum_{n=1}^{N}(CAR_{L,i,t} - ACAR_{L,t})^2}{2(N-1)} \tag{4.8}$$

Furthermore, in order to find whether for any week, t, the average residual return makes a contribution to either $ACAR_{Wt}$ or $ACAR_{Lt}$ one can test whether it is significantly different from zero (De Bondt and Thaler 1985) with:

$$t_{2tW} = AR_{W,t} /(s_t / \sqrt{N}) \tag{4.9}$$

where s_t is:

$$s_{tW} = \sqrt{\sum_{n=1}^{N}(AR_{W,n,t} - AR_{W,t})^2 / N - 1} \tag{4.10}$$

Similarly, for the loser portfolio one can use:

$$t_{2tL} = AR_{L,t} /(s_t / \sqrt{N}) \tag{4.11}$$

where s_t is:

$$s_{tL} = \sqrt{\sum_{n=1}^{N}(AR_{L,n,t} - AR_{L,t})^2 / N - 1} \tag{4.12}$$

In addition, in order to test whether loser portfolios outperform winner portfolios consistently for each testing period, that is whether the difference $ACAR_{Lt}$-$ACAR_{Wt}$, (define it as $ACAR_{CS}$) is statistically different from zero, without assuming that CAR_{Lt} and CAR_{Wt} are independent of each other as in the above tests (Rodriguez & Fructuoso 2002), the following t-statistic can be used:

$$t_{3t} = \frac{ACAR_{CS,t}}{s_{CS,t} / \sqrt{N}} \tag{4.13}$$

where:

$$s_{CS,t} = \sqrt{\frac{\sum_{i=1}^{N} (CAR_{CS,i,t} - ACAR_{CS,t})^2}{(N-1)}} \tag{4.14}$$

To evaluate whether the length of the formation and testing periods affect results, the above tests are repeated for other strategies as well, for a:

- 1-year formation and 2-year testing strategy resulting in 5 testing periods,
- 1-year formation and 3-year testing strategy resulting in 3 testing periods,
- 2-year formation and testing strategy resulting in 5 testing periods, and a
- 3-year formation and testing strategy resulting in 3 testing periods.

4.2.2 Contrarian profits above the risk free rate of return

This section performs all the tests of the previous one, using risk-free rate adjusted returns however. The only methodological difference from the previous section is the way U_t for each stock is obtained:

$$U_{it} = R_{it} - Rf_t$$

where:

U_{it} is now the above risk free rate excess return of stock i at time t, and

Rf_t is the risk free rate of returns at the same time.

The results will not be analysed since they are virtually identical to the ones obtained for market-adjusted returns. This is obvious by observation of figures 4.18 to 4.20 and Table 4.24 (Panel C) in the Appendix to this chapter, where the ACARS for the 1year, 2year, and 3year formation and testing strategies are plotted respectively. If one contrasts these figures to the ones for the market-adjusted returns one will not be able to tell the difference in most cases.

4.2.3 Contrarian profits using risk adjusted returns

As mentioned, one of the main questions in the literature is whether the perceived contrarian profits are just compensation for carrying an excess amount of risk, and as such they are not really above-risk profits. There has been an extensive discussion in the overreaction literature, which has shown that in order to draw any reliable scientific conclusions one must take in to account risk (see Ball & Kothari 1989). When Chopra, Lakonishok & Ritter (1992) for example use the Sharpe-Linter CAPM they find that profits due to overreaction are much less than when risk is not accounted for. On the other hand, De Bondt and Thaler (1985) suggest that losers not only outperform winners in the test period, but at the same time they are less risky, and as such, their differences with winners in returns will be more pronounced when risk is considered. The thesis tries to determine whether the one or the other explanation holds for the ASE, and the extent to which it does hold, before it attributes any results to overreaction.

In order to adjust for systematic risk the whole process in 4.2.1, is repeated for returns adjusted for systematic risk, that is, the risk-adjusted return, e_{it}, for every stock i is obtained from the following regression, under the assumption that returns are generated by the Sharpe-Lintner CAPM, and the usual assumptions for OLS estimators being best linear unbiased estimators:

$$R_{it} - R_{Ft} = a_{it} + b_{it}(R_{Mt} - R_{Ft}) + e_{it} \tag{4.15}$$

where:

R_{Ft} is the risk free rate of return at time t (proxied by the 3 month T-Bill)

α_{it} is a constant, or Jensen's alpha

b_{it} is the CAPM Beta: $\mathrm{b_{it}} = \dfrac{Cov(R_i, R_M)}{Var(R_M)}$

e_{it} is a normally distributed random error term with a zero mean and a constant variance

4.2.4 Contrarian profits using time-varying risk

The specification of returns in (4.15), while improving upon the market-adjusted returns and the risk-free rate excess returns by adjusting for systematic risk, also assumes that it is constant for the whole period. However according to Ross (1989), information arrives in the market stochastically and thus beta evolves in the same way. Yet, the contrarian literature has considered time variation in risk in very few cases, and even when it has done so, most times risk is assumed to change once between every formation and holding period, like is done for example by Lakonishok, Shleifer & Vishny (1994).

It is thus important to consider continuous time variation in risk in order to cover the gap in the overreaction literature as regards this issue. (1) If the chapter finds that considering time variation in risk does take away any profits, then this might indicate that all studies that have not employed continuous risk variation, could have found unrealistic results due to their assumption that risk is constant for all the sample period, or that it changes once every year or few years. (2) If however the chapter finds that time variation in risk does not explain results, this will also be an important result for the literature, because it will verify overreaction under more stringent criteria. In any case, results will have a number of implications and will address a major gap in the literature.

In order to account for the time-varying nature of systematic risk, contrarian profits are re-estimated, by viewing equation (4.15) as a time-varying parameters model, and the coefficient on the risk premium, b_{it}, is estimated using the Kalman Filter algorithm (Kalman 1960, 1963). This is a recursive algorithm for dynamic linear models evaluation, and the idea is to express a dynamic system in the state-space representation (see for example Hamilton 1994). In general the dynamic linear models basic assumptions are:

$$Z_t = A_t Z_{t-1} + w_t \tag{4.16}$$

$$Y_t = c' Z_t + v_t \tag{4.17}$$

Where the Z's are called states and (4.16) is known as the *state* equation or "system equation" and describes how the vector of states evolves over time. Equation (4.17) is called the *measurement* or "observation equation" and relates observable Y variables to the unobservable states. w_t and v_t are the shocks to the state and the measurement errors, respectively, and the c and A matrices are usually time invariant.

This chapter uses the following specification on the systematic risk adjusted residuals (equation (4.15)). First, define the vector of coefficients at time *t* as b_t. Then the measurement equation is:

$$y_{it} = X_{it} b_{it} + u_{it} \tag{4.18}$$

In addition, the state vector follows a process, which allows the time varying parameter to be generated stochastically by the transition equation:

$$b_{it} = b_{i,t-1} + k_{it} \qquad k_{it} \sim N(0, \sigma_k^2) \tag{4.19}$$

Where the variance of u_{it} is n_{it}, var(k_{it})= M_{it}, u_{it} and k_{it} are independent and n_{it}, M_{it} are assumed to be known. If one has an estimate of b_{it-1} using information through t-1 (denoted $b_{t-1|t-1}$) and its covariance matrix $\Sigma_{it-1,}$ then the updated estimate given y_{it} and X_{it} is:

$$S_{it} = \Sigma_{it} + M_{it} \tag{4.20}$$

$$\Sigma_{it} = S_{it} - S_{it} X'_{it}(X_{it} S_{it} X'_{it} + n_{it})^{-1} X_{it} S_{it} \tag{4.21}$$

$$b_{it|it} = b_{it-1|it-1} + S_{it} X'_{it}(X_{it} S_{it} X'_{it} + n_{it})^{-1} (y_{it} - X_{it} b_{it-1|it-1}) \tag{4.22}$$

Furthermore, the residuals are computed as recursive residuals, that is they are a series of normalised one-step Kalman Filter forecast errors:

$$\frac{(y_t - X_t b_{t-1|t-1})}{\sqrt{n_t + X_t(\Sigma_{t-1} + M)X_t'}} \tag{4.23}$$

Due to the specification in (4.19) the risk-adjusted returns are estimated allowing for an important characteristic of beta risk: *time variation* (Durbin and Koopman 2001, p.54). The intuition behind this specification is that betas change in response to new information. As shall be seen in the next section, this has important implications for the results and for previous studies on contrarian profits that do not allow for the effect of time on systematic risk.

All the above tests are repeated excluding the month of January in order to test for the well documented January effect (Rozeff and Kinney 1976), according to which returns during January are higher than returns of other months. This is done after De Bondt and Thaler (1985) found evidence that most of the jumps in contrarian profits occur during January. In addition, Gultekin and Gultekin (1983) found for the US and sixteen other markets, that returns are higher in all cases (although a bit lower for the US) in January compared to other months. Keim (1989) connects the January effect to microstructure biases and the size effect, explaining why January abnormal returns are higher for smaller firms compared to larger ones. In the overreaction area, Zarowin (1990) finds no overreaction effect out of January after controlling for size. On the other hand, it has been shown in many other cases, that although contrarian profits are higher in January, the overreaction profitability is not preliminary a January effect. For example, Jegadeesh (1990) finds abnormal returns of 4.37% in January and 2.2% out of the month of January (see for other examples De Bondt & Thaler 1987, and Pettengill & Bradford 1990).

4.2.5 Systematic risk differentials between formation and testing periods

As discussed earlier, Chan (1988), and Ball and Kothari (1989) argue that the overreaction effect is due to changes in the equilibrium required returns, for which De Bondt and Thaler (1985) did not control. Since the profitability of contrarian strategies is based on the reversal of the formation period returns during the testing period, it is crucial to examine whether there is also a reversal in risk between the two periods. For example, Chan (1988) addresses this point for US data and suggests that excess returns realized by investors are likely to be a normal compensation for risk. Here, a similar process to the one in Chan is employed to empirically evaluate whether there are systematic risk changes between formation and testing periods for the ASE. This will also allow the reader to evaluate whether the above method (used in many studies) captures risk changes better than the Kalman filter that is suggested by the present thesis. That is, the following regression is estimated:

$$R_{it} - R_{Ft} = a_{1i}(1 - D_t) + a_{2i}D_t + b_i(R_{Mt} - R_{Ft}) + b_{iD}(R_{Mt} - R_{Ft})D_t + e_{it} \quad (4.24)$$

where:

$t = 1$ to 104, for the 1 year formation and 1 year testing strategy

$t = 1$ to 208, for the 2 year formation and 2 year testing strategy

$t = 1$ to 312, for the 3 year formation and 3 year testing strategy

D_t is a dummy variable:

$$D_t = \begin{matrix} 0, t \leq 52 \\ 1, t > 52 \end{matrix}$$ for the 1 year formation and 1 testing strategy

$$D_t = \begin{matrix} 0, t \leq 104 \\ 1, t > 104 \end{matrix}$$ for the 2 year formation and testing strategy

$$D_t = \begin{matrix} 0, t \leq 156 \\ 1, t > 156 \end{matrix}$$ for the 3 year formation and testing strategy

e_{it} is a random error term $e_{it} \sim N(0, \sigma_{i1}^2)$ for the formation period and $\sim N(0, \sigma_{i2}^2)$ for the testing period ($\sigma^2_{\iota 1}$ & $\sigma^2_{\iota 2}$ don't have to be different).

Equation (4.24) allows estimation of different coefficients for formation & testing periods. For example, the mean abnormal return in the formation (testing) period is estimated by a_{1i} (a_{2i}[66]), while the formation period systematic risk is estimated by b_i and the testing period systematic by $(b_i + b_{iD})$.

If b_{iD} is not different from zero, then both the formation and testing period have the same beta and Chan's explanation that results are due to beta differences between formation and testing periods cannot hold[67]. Note however, that although beta might change, Chan's method assumes it to change only once a year or every few years, which might not be appropriate. Furthermore, if profits are more significant than those obtained by the Kalman filter, this could suggest the superiority of this method[68] compared to Chan's.

4.2.6 The mean-variance efficiency of the market portfolio systematic risk

The chapter uses the ASE General Price Index as a proxy for the local market portfolio. However, no evidence exists about its mean variance efficiency. Thus, as a first step in the analysis, ASE's mean-variance efficiency is evaluated with a range of test statistics such as the Gibbons, Ross and Shanken (1989) statistic and also a Generalised Method of Moments (GMM) statistic (see Hansen, 1982), which makes weaker distributional assumptions and is therefore more robust, given the documented non-normality of financial data. One way to test mean-variance efficiency (see for example Fletcher 1994) is to use a linear regression model:

$$R_{it} = \alpha_{im} + \beta_{im} R_{mt} + \varepsilon_{it} \qquad (4.25)$$

[66] Due to the assumption made for the residuals variance, the α's should not be different from running regression 4.15 separately for the formation and the testing period.

[67] Chan's explanation will not also hold if the betas of both losers and winners move in a similar manner. This will cancel out the beta effect, and discard the suggestion that increased risk for losers in conjunction with decreased risk for winners is responsible for profits.

[68] Since our method will have accounted for some profits owed to changes in risk, that are perceived as contrarian profits under Chan's method.

for all i=1,....,N. The residuals have a zero mean and zero covariance with the evaluated portfolio (R_{mt}), while N here denotes the number of assets used in the evaluation. If the market portfolio is efficient, the constant term should not be statistically different from zero, for all assets. Gibbons, Ross and Shanken (1989) demonstrate that under the null hypothesis of α_{im}=0 the test statistic $Q= [(T-N-1)/N]\,W$ will be distributed as a central F distribution with N and $(T-N-1)$ degrees of freedom, where $W = \dfrac{\alpha_m{}'\Sigma^{-1}\alpha_m}{(1+\Theta_m^2)}$ and $\Theta_m^2 = \dfrac{R^*{}_m}{\sigma_m}$. Note that R_m^* is the sample mean excess return of the portfolio being evaluated; σ_m is the maximum likelihood estimate of the sample standard deviation, while Σ is the maximum likelihood estimate of the residual covariance matrix.

MacKinlay and Richardson (1991), and Clare, Smith and Thomas (1997) employ a GMM procedure to test for the mean-variance efficiency of USA and UK portfolios respectively, and in both studies, the results of the traditional OLS are reversed when the more robust GMM approach is employed. Clare *et al.* show that (if β_0 is the true value of β, and Z_{t+1} is a vector of instruments) in the restricted version of the above equation (where α_i=0, for all i) the estimation method constructs a vector of innovations $\varepsilon_{t+1}(\beta)$, which have the property $E_t[\varepsilon_{t+1}(\beta_0)|Z_{t+1}] = 0$ and then chooses parameters that set linear combinations of the moment condition $E_t[\varepsilon_{t+1}(\beta) \otimes Z_{t+1}] = 0$ (p.648). Testing mean variance efficiency, in this case, is the test of the over identifying restrictions generated by these orthogonality conditions. This test is shown by Hansen (1982) to be distributed as a χ^2(n), where n is the number of orthogonality conditions (the J-statistic).

Here, both statistics are employed and for the empirical tests two sets of assets are used, that is, four portfolios formed based on market capitalisation and five industry portfolios. The size portfolios are equally weighted, annually rebalanced, and for their construction, all stocks listed in the ASE that had continuous price observations for the entire sample period are used. The industry portfolios are the ASE Industrial, Banking, Insurance, Tobacco and Construction Indices. In the GMM case the vector of instruments is made up by the constant and the excess return on the market. Since there are two instruments and four size portfolios, i.e. four equations (five when industry portfolios are considered) the equation system generates eight orthogonality conditions (ten when industry portfolios are considered). However, setting a_i=0 reduces the number of parameters estimated to four (five when industry portfolios are considered), thus the *J*-statistic is distributed as $\chi^2(4)$ [or $\chi^2(5)$ when including industry portfolios]. Note that the unrestricted system is also estimated and a Wald statistic is then used to test the restriction that a_i=0.

With respect to the methodology, this chapter determines whether the ASE General Price Index is an efficient portfolio, and then uses it to test for the profitability of contrarian strategies in the ASE. Two extreme portfolios and three different definitions of excess returns are employed using five different time horizons. Seasonal cffects are considered. Static risk (CAPM adjusted returns), time varying-risk between formation and testing periods (Chan 1988), and continuous time-variation in risk (Kalman filter), are also considered.

4.3 Results

4.3.1 Sample statistics & normality tests

Table 4.1 presents the descriptive statistics (mean, standard deviation, skewness, kurtosis, and the Jarque-Bera test of normality) on the winner and loser portfolios formed by using Market adjusted returns[69].

Table 4.1
Sample statistics of Winner (W) and Loser (L) Portfolio
(Market adjusted returns, 1-year formation & testing periods)

Period	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A							
Sample statistics of Winner (W) portfolio using Market-adjusted returns [u_i=R_{it}-R_{Mt}]							
90-91	0.001082	0.034470	-0.1045	0.083002	-0.5787	2.09776	12.43705
91-92	0.013444	0.068341	-0.26815	0.224068	-0.59712	6.13466	84.6306
92-93	-0.00061	0.030951	-0.09422	0.068694	-0.81186	1.66535	11.72133
93-94	-0.01085	0.045001	-0.13969	0.138973	0.02006	3.19029	22.05566
94-95	-0.00318	0.028122	-0.07509	0.056817	-0.32171	-0.0181	0.89767
95-96	-0.00657	0.031187	-0.06948	0.082437	0.62907	0.63761	4.31048
96-97	0.001464	0.029526	-0.04108	0.075181	0.72689	-0.084	4.59454
97-98	-0.00028	0.041567	-0.15585	0.122402	-0.32712	3.85477	33.12242
98-99	0.013537	0.051991	-0.14665	0.141922	-0.32846	1.12817	3.69272
99-00	-0.01114	0.049519	-0.10512	0.104939	0.52691	0.25472	1.66519
Panel B							
Sample statistics of Loser (L) portfolio using Market-adjusted returns [u_i=R_{it}-R_{Mt}]							
90-91	0.000435	0.032205	-0.1296	0.071893	-1.18677	5.2804	72.61879
91-92	-0.00045	0.040173	-0.07693	0.146368	1.20665	3.52229	39.4994
92-93	0.018877	0.043482	-0.08347	0.147763	0.53602	0.84406	4.0337
93-94	3.79E-05	0.048285	-0.08521	0.225858	1.86014	8.34653	180.9276
94-95	-0.00017	0.038721	-0.10083	0.095717	-0.24321	1.43648	4.98351
95-96	-0.0086	0.031717	-0.1212	0.071253	-0.59022	2.46318	16.16489
96-97	-0.00755	0.050375	-0.13116	0.098452	-0.06932	-0.0563	0.04853
97-98	-0.01029	0.059232	-0.22168	0.178421	-0.14779	3.48801	26.54936
98-99	0.03822	0.087622	-0.20983	0.225341	-0.31945	0.32551	1.11401
99-00	0.000754	0.017133	-0.03949	0.028515	-0.33995	-0.5338	1.05861

For the 1-year formation and testing strategy, the highest mean return for the winner portfolio is in 1998-1999 (0.0135). The previous year, i.e. the year the portfolio was formed, is a period of high volatility for ASE (see section 4.3.7, Figure 4.8/Table 4.15), and could probably be due to this. This pattern is further elucidated by the fact that the second highest return for the winners is for 1991-1992 (0.0134), which has the highest standard deviation as well (0.0683), and its formation year was the second most volatile for ASE up to 1999. Six out of ten years, the winner portfolio experiences negative mean returns, the lowest observed in the 1999-2000 portfolio (-0.0111), followed closely by the second lowest in 1993-1994 (-0.0109). The skewness statistic, which indicates the degree of -or lack of- symmetry of a distribution, as well as the Kurtosis statistic, which indicates the extend to which a distribution is peaked or flat, show that half of the portfolios returns may not be drawn from a normal distribution. This is confirmed by the Jarque-Bera[70] test of normality, where only half of the portfolios pass the test at the 5% level of significance. For losers, the highest mean returns (0.0382) are observed in the same periods as for the winners (which could also be due to formation period volatility. Section 4.3.7 will elaborate), but the highest standard deviation (0.0876) is now for the portfolio with the highest mean returns. The lowest mean return for losers (-0.0103) is exhibited for the 1997-1998 period, which also exhibits the second larger standard deviation (0.059). With respect to normality, there is no significant difference from winners; four portfolios pass the Jarque-Bera test of normality at the 5% level of significance, and one at the 10% level.

[69] The same statistics for the risk adjusted, and the time varying-risk adjusted returns are presented in the Appendix of this chapter tables 4.18 to 4.23.

Table 4.2
Sample statistics of Winner (W) and Loser (L) Portfolio
(Market adjusted returns, 2-year formation & testing periods)

Period	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A Sample statistics of Winner (W) portfolio using Market-adjusted returns [u_i=R_{it}-R_{Mt}]							
90-91	0.007768	0.052794	-0.24516	0.211979	-0.43529	6.43624	182.7933
92-93	-0.00574	0.035555	-0.11483	0.103138	0.18155	1.58628	11.47524
94-95	-0.00494	0.032882	-0.08236	0.102231	0.39249	0.78353	5.33053
96-97	0.007534	0.036086	-0.14718	0.088089	-0.76503	2.44538	36.0575
98-99	-0.01312	0.044381	-0.08434	0.089137	0.66616	-0.0219	2.51541
Panel B Sample statistics of Loser (L) portfolio using Market-adjusted returns [u_i=R_{it}-R_{Mt}]							
90-91	0.006301	0.036344	-0.06575	0.112562	0.60699	0.3562	6.93603
92-93	-0.00344	0.043785	-0.10319	0.216391	1.15499	5.20874	140.6901
94-95	-0.00753	0.053497	-0.15328	0.135705	0.09323	0.11379	0.20676
96-97	0.014697	0.080135	-0.2495	0.234227	0.01665	0.62454	1.69502
98-99	-0.00116	0.02138	-0.03943	0.050296	0.45143	-0.4508	1.44267

For the 2-year formation and testing strategy in Table 4.2, there are five winner and loser portfolios. Apart for the first and fourth portfolio all others demonstrate negative mean returns for both winners and losers. For the winners the highest mean return (0.0078) is encountered in 1990-1991 period, while for the losers it comes in the 1996-1997 period, been much higher (0.0147). Both these periods experience the highest standard deviation, while the second highest standard deviation belongs to the lowest mean returns, which are met in the 1998-1999 portfolio for winners and 1994-1995 for losers. The two highest return portfolios have the highest degree of kurtosis and fail the normality test.. Two winner and three loser portfolios pass the normality test.

[70] The Jarque-Bera test of normality is always distributed as a χ^2 (2) under the null hypothesis of the residuals been normally distributed. The 5% critical value of the χ^2 (2) is 5.99, while the 10% critical value of the χ^2 (2) is 4.61.

Table 4.3
Sample statistics of Winner (W) and Loser (L) Portfolio
(Market adjusted returns, 3-year formation & testing periods)

Period	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A							
Sample statistics of Winner (W) portfolio using Market-adjusted returns [u_i=R_{it}-R_{Mt}]							
90-92	0.00564	0.028924	-0.09601	0.083221	-0.46798	1.07669	13.22929
93-95	-0.0074	0.038575	-0.13537	0.114402	0.43664	1.03774	11.95691
96-98	-0.0011	0.029892	-0.06913	0.081727	0.52426	0.13269	4.00255
Panel B							
Sample statistics of Loser (L) portfolio using Market-adjusted returns [u_i=R_{it}-R_{Mt}]							
90-92	0.002849	0.037899	-0.10371	0.113672	0.52517	0.49424	8.7587
93-95	-0.00213	0.063147	-0.33606	0.194497	-0.77842	5.39116	204.6745
96-98	0.017067	0.08999	-0.26194	0.286421	0.03584	0.72205	1.88658

Table 4.3 presents the sample statistics for the 3-year formation and testing strategy. The first and the last period's portfolio have the highest average returns for winners and losers respectively. The lowest standard deviation (0.0289) for winners is related to the best mean-performing portfolio for the period 1990-1992, while for losers the best performing portfolio is the one created using data from period 1996-1998 and has the highest standard deviation (0.09). Although two out of three portfolios fail the normality test, looking at skewness and kurtosis indicates that apart for the second loser portfolio, problems with the return distribution are not as severe here, probably due to the 156 available observations here, compared to 104 and 52 for the other two strategies. For the latter, possible normality problems suggest that results are discussed with caution.

4.3.2 Testing the mean variance efficiency of the ASE General Price Index

Table 4.4 presents the *Q*-statistic, the GMM *J*-statistic from the restricted system, and a Wald test from the GMM estimated unrestricted system, for both sets of portfolios[71]. More specifically, for all methods and for both sets of assets the null hypothesis of mean variance efficiency for the ASE General Price Index is not rejected. This indicates that the chapter can use the ASE General Price Index as a proxy for the market portfolio.

Table 4.4
Testing Mean-Variance Efficiency

	Portfolios	
	Size portfolios	**Industry portfolios**
OLS Q-statistic	1.1388 ($F^{0.05}_{4,498} = 2.37$)	0.34671 ($F^{0.05}_{5,498} = 2.18$)
GMM J-statistic (restricted case)	4.6831 ($\chi_4^{2(0.05)} = 9.49$)	2.7312 ($\chi_5^{2(0.05)} = 11.07$)
GMM Wald-statistic (unrestricted case)	4.4993 ($\chi_8^{2(0.05)} = 15.51$)	2.8432 ($\chi_{10}^{2(0.05)} = 18.31$)

[71] Descriptive statistics of the portfolios used, can be found in the Appendix Table 4.17.

4.3.3 Contrarian profits

Table 4.5 reports the ACARs for the winner and loser portfolios for the three different specifications of returns, the profits of the contrarian strategy [$ACAR_{Lt}$-$ACAR_{Wt}$], as well as the *t*-statistics, for three different formation-testing periods, as outlined earlier[72]. The findings indicate that prior losers seem to outperform prior winners in all cases. When returns are defined as market-adjusted (Panel A), the contrarian Average Cumulative Abnormal Returns are all positive, but they are not statistically significant. For example, the highest difference between $ACAR_{Lt}$ and $ACAR_{Wt}$ (0.1888) is for the 3-year formation and testing strategy, the second highest is for the 2-year formation and testing strategy (0.1405), and the third highest for the 1-year formation and testing strategy (0.1298).

However, when returns are defined as in (4.15), i.e. adjusted for systematic risk (Panel B), the profits of the contrarian strategy become statistically significant at the 5% level of significance for both the 3-year formation and testing strategy (t_{3t}-statistic: 2.872) and the 2-year formation and testing strategy (t_{3t}-statistic: 2.330). In addition, note that the economic magnitude of the profits increases significantly: for the 2-year formation and testing horizon, profits increase from 0.1405 when returns arc defined as market-adjusted to 0.4748 now, while for the 3-year formation and testing horizon, they increase from 0.1888 when returns are defined as market-adjusted to 1.8489 now. Note also that, for the first time, along with t_{3t} (that tests whether $ACAR_{Lt}$-$ACAR_{Wt}$ is statistically

[72] See also in the Appendix Table 4.24 for other formation and testing period results, and Risk free rate adjusted returns.

different from zero without assuming that CAR_{Lt} and CAR_{Wt} are independent of each other) t_{1t} is also statistically significant for the 3-year formation and testing strategy (t_{1t}-statistic: 3.844).

Table 4.5
Contrarian Profits in the ASE

	$ACAR_{Wt}$	$ACAR_{Lt}$	$ACAR_{CES}$ (t_{3t})	$ACAR_{Lt}$-$ACAR_{Wt}$ (t_{1t})
		Panel A **Market-adjusted returns [u_i=R_{it}-R_{Mt}]**		
1year testing period	0.04644	0.17623	0.12980 (0.624)	0.12980 (0.475)
2year testing period	0.12031	0.26085	0.14054 (0.792)	0.14054 (0.279)
3year testing period	-0.13312	0.05567	0.18879 (0.523)	0.18879 (0.301)
		Panel B **Systematic risk-adjusted returns [e_i=(R_{it}-R_{Ft})-a–β_{it}(R_{Mt}-R_{Ft})]**		
1year testing period	-0.02815	0.14222	0.17037 (0.816)	0.17037 (0.535)
2year testing period	-0.10446	0.37035	0.47481 (2.330)*	0.47481 (0.927)
3year testing period	-1.10753	0.74142	1.84895 (2.872)*	1.84895 (3.844)*
		Panel C **Time-varying systematic risk-adjusted returns [Kalman Filter]**		
1year testing period	0.01986	0.01929	-0.00058 (-0.004)	-0.00058 (-0.002)
2year testing period	-0.15364	0.29872	0.45235 (1.720)**	0.45235 (0.783)
3year testing period	-0.49260	-0.47310	0.01950 (0.036)	0.01950 (0.048)

Notes to Table 4.5:

t-statistics appear in parenthesis

- * denotes significance at the 5% level
- ** denotes significance at the 10% level

The above results are consistent with the suggestion of De Bondt & Thaler (1985) that losers not only outperform winners, but they are less risky as well. The increase in the performance of the zero-investment portfolio when using risk-adjusted returns compared to results when using market-adjusted returns is explained by this argument exactly. More specifically, when market-adjusted returns are employed, the beta is assumed equal to one for all stocks and portfolios. This depresses the performance of losers and exaggerates the performance of winners, since it compares the performance of two positions with a different amount of risk, as if they had the same. When however risk is taken into account this is corrected and the less risky loser portfolio returns are increased, while the more risky winner portfolio returns are depressed. As a result, the differences in performance are more pronounced, becoming not only higher, but also more significant.

The fact however that systematic risk (beta) is considered to be constant for the whole sample period is somehow unrealistic, and although it might be more efficient compared to using market adjusted returns, it might still not properly describe asset returns, and could thus draw a false picture of a continuously changing reality. That is why overreaction is next examined after relaxing the constant risk assumption.

When contrarian profits are estimated from returns adjusted for time-varying systematic risk, using the Kalman Filter (Panel C), only the two-year formation and testing strategy appears significantly profitable at the 10% level of significance in the ASE (t_{3l}-statistic: 1.720). For the remaining Kalman filter adjusted returns, neither the t_{3r}-statistic nor the t_{1r}-statistic is significant. Furthermore, the economic profits from all strategies appear significantly reduced: the profits of the 1-year formation and testing strategy fall from 0.1704 to -0.0006 and the profits of the 3-year formation and testing strategy fall from 1.8489 to 0.0195 when accounting for the time-varying nature of systematic risk. The exception is the 2-year formation and testing strategy for which the profits remain virtually the same, and that is important, since it is the only statistically significant strategy.

The above finding is consistent with Chen and Sauer (1997) who also find that changes in risk affect contrarian profits. This has very important implications for all the tests connected with this strand of research in finance. If these findings are correct, then all the studies performed in the past that have not considered continuous time variation, might have found biased results, or at least have exaggerated their results. This would indicate that in the majority or in some cases, most of the profits attributed to overreaction might just be due to risk changes from one period to another.

These results are reinforced when one visually examines the piots of different ACARs. For example, Figure 4.1 in the next page presents the ACARs of the winner (W) and of the loser (L) portfolios for the risk-adjusted returns, while Figure 4.2 presents ACARs for the Kalman Filter adjusted returns, for the 1-year formation & testing strategy.

Figure 4.1
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 1-year formation & testing periods)

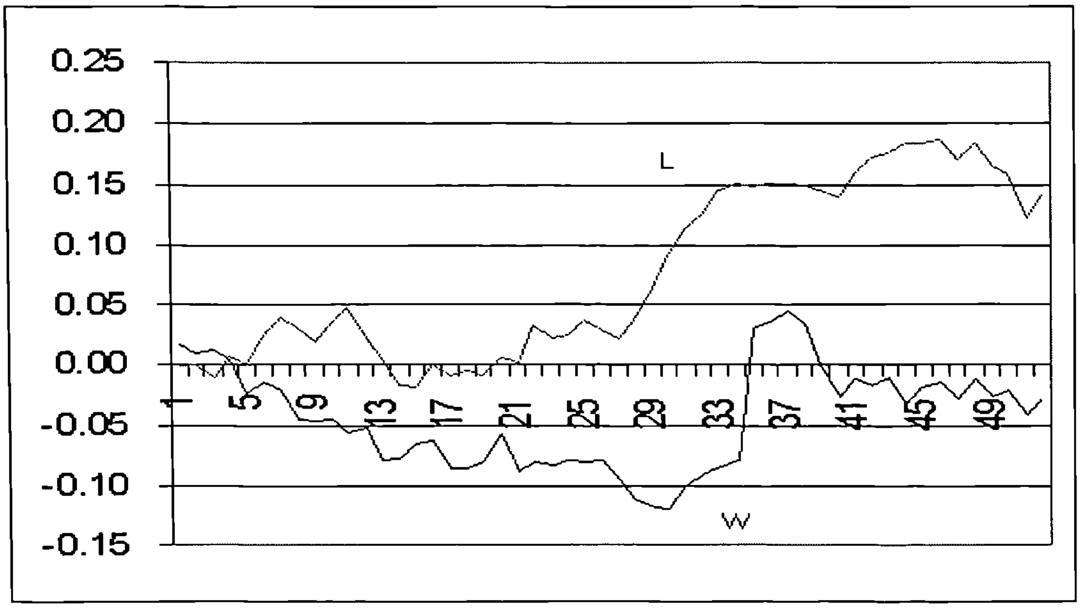
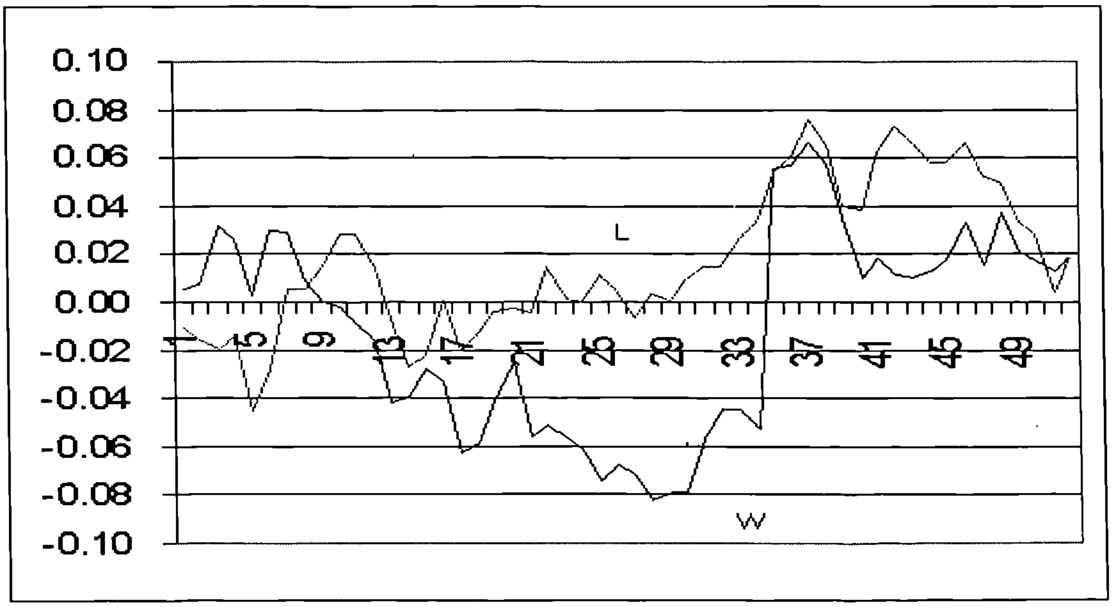


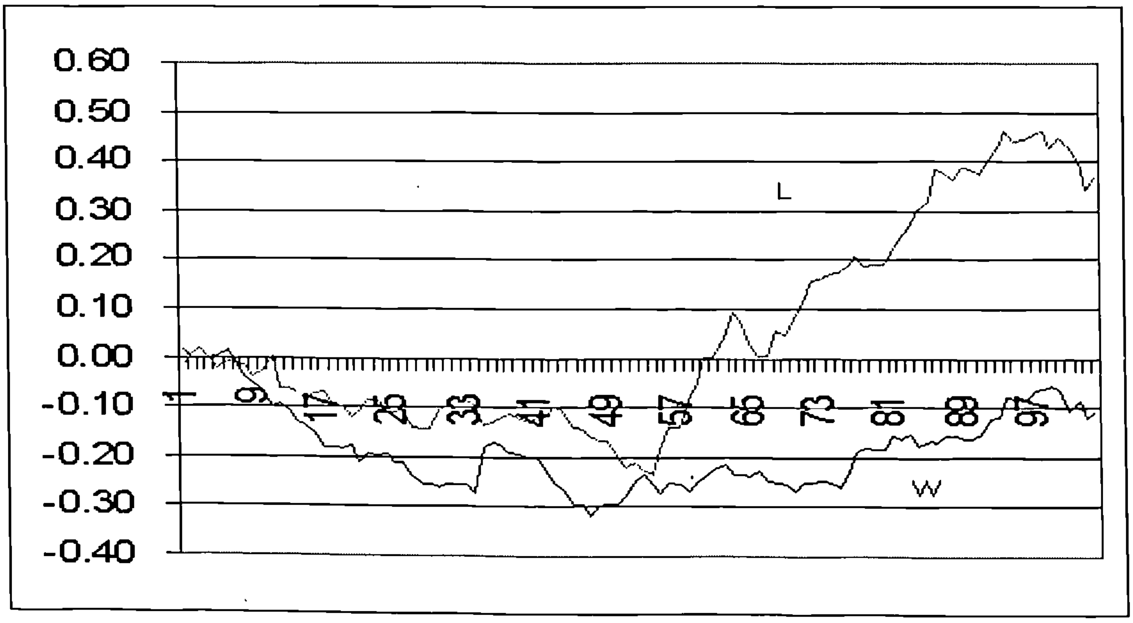
Figure 4.2
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 1-year formation & testing periods)



As can be seen in Figure 4.1, the ACARs of the loser portfolio are positive and the ACARs of the winner portfolio are negative, for nearly the complete testing period. However, when one examines the ACARs obtained from the Kalman Filter returns, the magnitude the ACARs of both portfolios is strikingly smaller (while the winner portfolio ACARs become positive after week 34).

As for other formation & testing periods: Figure 4.3 bellow, presents the ACARs of the winner (W) and loser (L) portfolios for the risk-adjusted returns, while Figure 4.4 in the next page, presents the same ACARs for the Kalman Filter returns, for the 2-year formation & testing period strategy. As can be seen in Figure 4.3, the ACARs of the loser portfolio become positive only after week 69, while the ACARs of the winner portfolio are consistently negative.

Figure 4.3
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 2-year formation & testing periods)



In Figure 4.4 however, although the past winner portfolio ACARs remain the same, the past loser portfolio ACARs are reduced significantly in magnitude compared to the risk adjusted returns, especially for the first two thirds of the investment horizon.

Figure 4.4
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 2-year formation & testing periods)

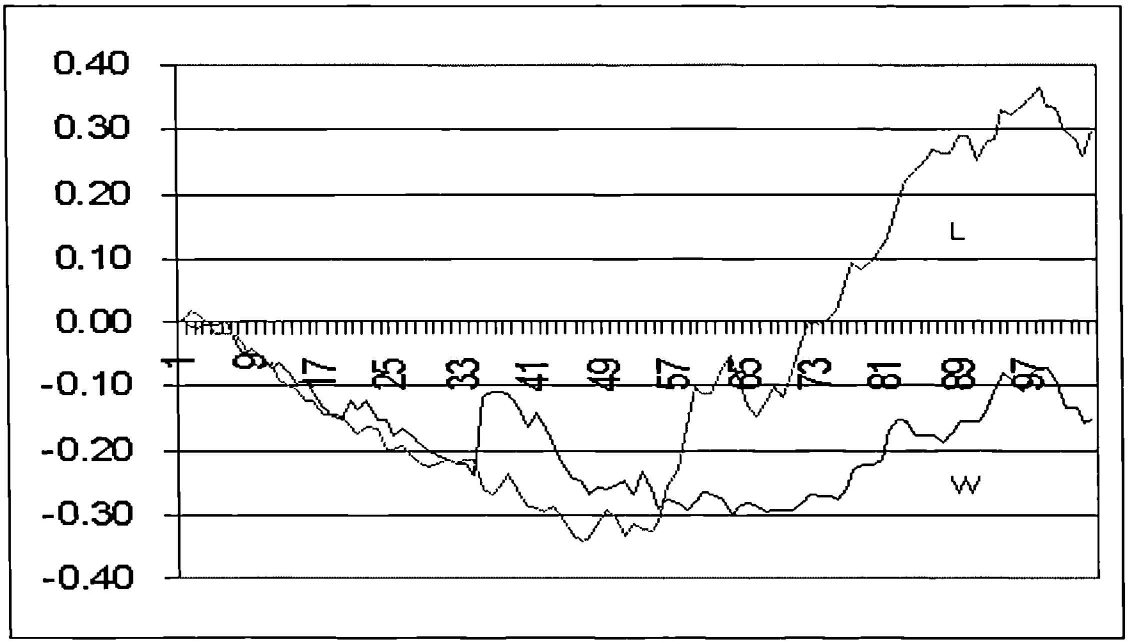


Figure 4.5 in the next page, contrasts the ACARs of the winner (W) portfolio to that of the loser (L) portfolio, employing risk-adjusted returns, while Figure 4.6 presents the same ACARs for the Kalman Filter returns (time varying risk-adjusted returns), for the 3-year formation & testing period strategies.

Figure 4.5
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 3-year formation & testing periods)

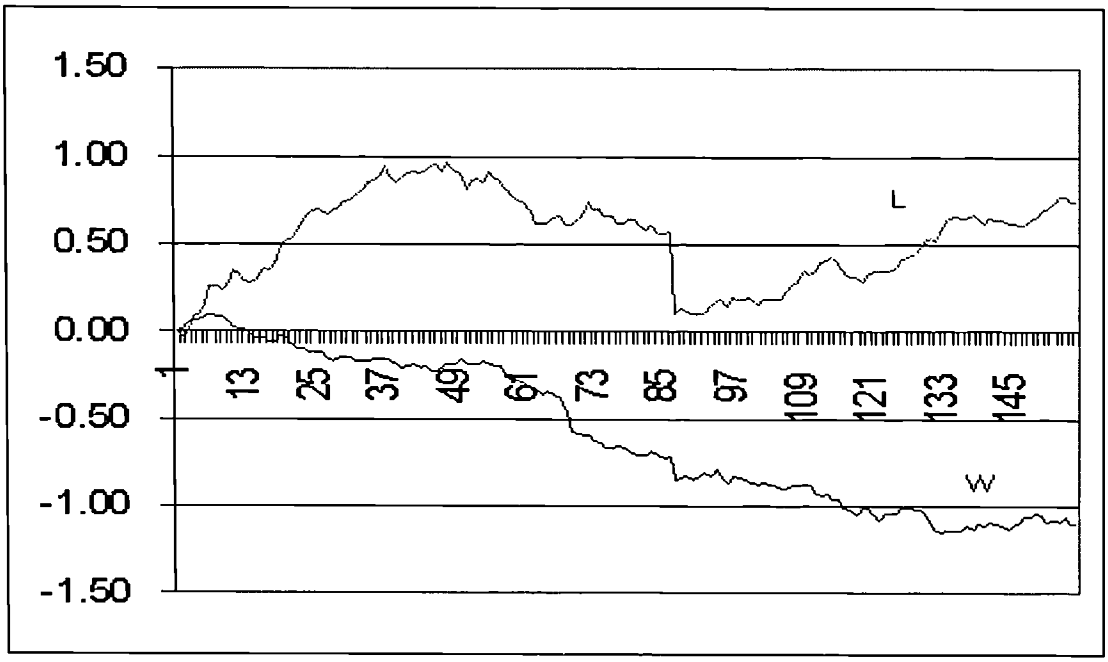


Figure 4.6
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 3-year formation & testing periods)

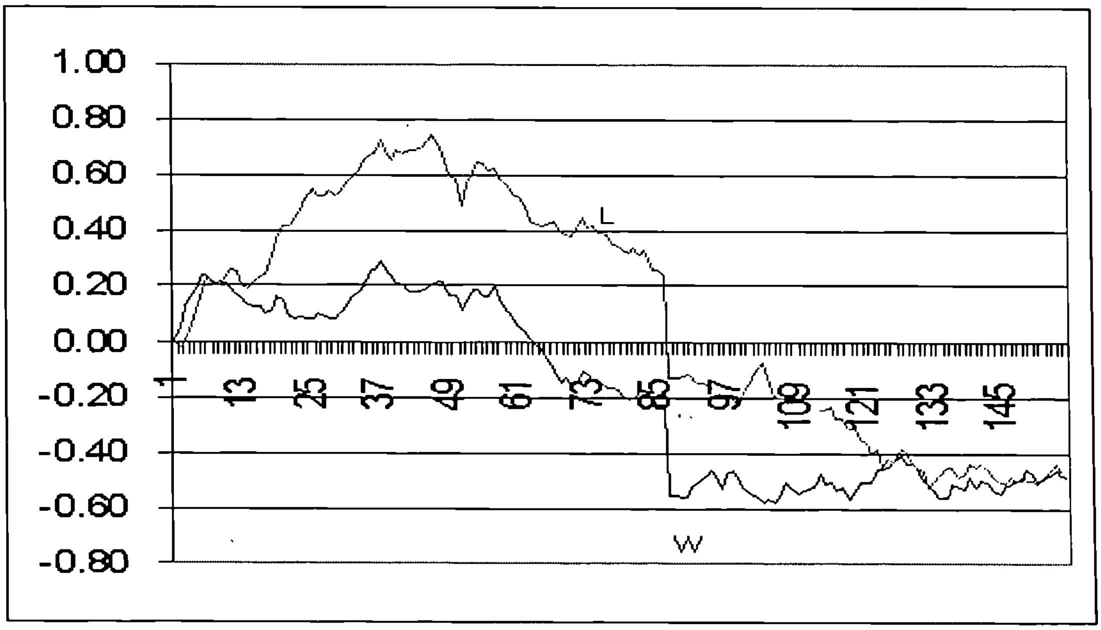


Figure 4.5 indicates that the ACARs of the loser portfolio are consistently positive, while those of the winner portfolio are consistently negative (as in the 2-year formation & testing strategy). At the same time, in Figure 4.6 both loser and winner ACARs shrink in magnitude, while the loser portfolio ACARs become negative after week 85 and the winner ACARs are positive until around week 70. The reader can find the figures of the remaining strategies that are based on all year round data (January to December every year) in the Appendix of this chapter (Figures 4.9 to 4.22). It becomes clear from observing the figures, that in most cases the most profitable strategy is the 3-year formation and testing strategy. It always outperforms the others in the first and second year, and does even better in the third year as well, apart for the sharp drop in August of the second year for Market adjusted returns, and which will be discussed later on.

Consistent with Chopra et al. (1992) who suggest that how returns are defined is important for the examination of contrarian profitability, the chapter finds that profits are sensitive to the definition of abnormal returns. More specifically, when returns are defined as market-adjusted the profits of contrarian strategies are not statistically different from zero, while when returns are adjusted for systematic risk, the profits of contrarian strategies are indeed both statistically and economically significant. However, taking into account time-variation of systematic risk to construct abnormal returns reduces significantly the profitability of contrarian strategies. The later shows that part of the profits but not all are due to changes in systematic risk, which could have been considered as genuine profits had the chapter not considered these changes.

4.3.4 The effect of January

The results of previous empirical studies suggest that stock returns behave differently during the calendar year. For example, it is suggested that stock returns in many national equity markets tend to be statistically significant and positive during the month of January (the *January Effect*, Rozeff and Kinney 1976). In the overreaction area, Chopra, Lakonishok & Ritter (1992) consider *seasonal effects*, De Bondt & Thaler (1985,1987) find that contrarian profits are higher in January, while Jegadeesh (1990) observes abnormal returns of 4.37% in January and 2.2% out of the month of January. In another study Pettengill & Bradford (1990), find two-thirds of abnormal returns to occur during January. It is thus crucial to determine whether the effect is present for our dataset as well and to measure the magnitude of the January seasonal if it does exist.

In order to investigate whether this seasonal effect has any implications for the results of the previous subsection, the chapter re-estimates the contrarian profits of all strategies, but *excluding* this time, the observations of the first four weeks of each year from the sample[73]. The results appear in Table 4.6 and seem to suggest that the January seasonal documented in the literature may have an effect (albeit small) in the profitability of contrarian strategies in the ASE.

[73] A dummy variable is also used for one of our strategies to account for the January effect. This should give us the same results on average as for when deleting the January observations, and so it did. Thus the chapter reports only the first case.

Table 4.6
Contrarian Profits in the ASE (Excluding January)

	$ACAR_{Wt}$	$ACAR_{Lt}$	$ACAR_{CES}$ (t_{3t})	$ACAR_{Lt}$-$ACAR_{Wt}$ (t_{1t})
	Panel A **Market-adjusted returns [u_i=R_{it}-R_{Mt}]**			
1year testing period	0.0531	0.18227	0.12917 (0.639)	0.12917 (0.569)
2year testing period	0.18700	0.30484	0.11783 (0.421)	0.11783 (0.256)
3year testing period	-0.88457	0.27383	0.36228 (0.720)	0.36228 (0.748)
	Panel B **Systematic risk-adjusted returns [e_i=(R_{it}-R_{Ft})-a–β_{it}(R_{Mt}-R_{Ft})]**			
1year testing period	-0.02817	0.21805	0.24622 (1.372)	0.24622 (0.842)
2year testing period	-0.15589	0.34269	0.49867 (2.448)*	0.49867 (1.083)
3year testing period	-0.71234	0.46882	1.18116 (2.677)*	1.18116 (3.451)*
	Panel C **Time-varying systematic risk-adjusted returns [Kalman Filter]**			
1year testing period	0.00333	-0.09351	-0.09684 (-0.842)	-0.09684 (-0.418)
2year testing period	-0.13890	0.16697	0.30588 (2.319)*	0.30588 (0.941)
3year testing period	-0.30077	-0.11103	0.18974 (0.405)	0.18974 (0.553)

Notes to Table 4.6:

t-statistics appear in parenthesis
- * denotes significance at the 5% level
- ** denotes significance at the 10% level

Weekly data, 1989-2001.

For example, when one examines the overall performance of the contrarian strategies the results in Table 4.6 are very similar to the ones in Table 4.5. Prior losers still outperform prior winners in all cases, apart for the one-year formation and testing strategy when using the Kalman filter adjusted returns.

Furthermore, when returns are defined simply as market-adjusted (Panel A), the ACARs are in all cases statistically insignificant, although they are positive for all periods as before. However, when returns are adjusted for systematic risk (Panel B), the profits of the contrarian strategy become statistically significant at the 5% level of significance for both the 3-year formation and testing strategy (t_{3t}-statistic: 2.677) and the 2-year formation and testing strategy (t_{3t}-statistic: 2.448). As before, the economic magnitude of the profits increases significantly, and along with t_{3t}, t_{1t} is statistically significant for the 3-year formation and testing strategy (t_{1t}-statistic: 3.451). When contrarian profits are estimated using the Kalman Filter (Panel C) the 2-year formation and testing strategy is again significant; however, this time at the 5% level (t_{3t}-statistic: 2.319) instead of the 10% level observed in Table 4.5.

The January effect does not explain contrarian profits for ASE, in fact it does not change the overall results from the ones observed when using the whole sample. There are slight changes in the magnitude of profits, but there is no pattern[74]. For example, the 2-year formation and testing horizon profits of panel B increase from 0.4748 that they were for all months in Table 4.5 to 0.4987 when January is excluded in Table 4.6. On the other hand, the 3-year formation and testing strategy profits fall from 1.8489 in Table 4.5, to 1.1812 in Table 4.6. It can thus be concluded, given that there are a lot of profits unexplained by January, that the January seasonal does not affect the data and the strategies employed in this chapter although losers (winners) performance falls (improves) slightly.

[74] See also Appendix Figures 4.23 to 4.33

4.3.5 The effect of August-September

A visual inspection of the profits for the winner portfolios (e.g. Figures 4.13, 4.14 in the Appendix) suggests an important shift in return behaviour during August. This is more profound for the two & three year testing periods, been indifferent to the formation period length, and it is visualised as a sharp drop for the past loser's ACAR.

The first point to be investigated is whether some extreme observations that might have been missed during the initial inspection for outliers, affected results. There were no outliers found; and only six observations (out of about 100,000, or 0.006%) were higher than average (moving up or down at about a 100% for a single week, and then followed a normal behaviour). These firms were however removed from the portfolios that they were included and were replaced with the next available ones that were not characterized by such large changes. Tests were then re-performed for the three-year formation and testing strategy that suffered the most serious drop, and for all three different types of returns. The results did not indicate any significant changes however. More specifically the ACAR figures were identical in two out of three cases and in the third very similar. The sharp drop in August was still present and of the same magnitude, showing that the drop is a common feature for all stocks in the loser portfolio, which might be due to an August effect as suggested by Draper and Paudyal (1997), or a loser effect in August.

In order to investigate whether this seasonal effect has any implications for the results in section 4.3.3, the chapter re-estimated the contrarian profits of all strategies, this time *excluding* the observations of the relevant month from each of the years in the sample. The results appear in Table 4.7, and according to them past losers still outperform past winners. The winner-minus-loser arbitrage profits for the three years formation and testing strategy (Panel A) become statistically significant (t_{1t}: 1.942) and larger (1.0742 compared to 0.1888 for the whole sample in Table 4.5) for the first time. The economic magnitude of the profits increases significantly in all but one case, where it drops slightly (3year formation and testing strategy, Panel B), and t_{3t}, is positive and statistically significant for all three horizons in the first and second panel. Along comes t_{1t} that is statistically significant for the 3year formation and testing strategy, and both the 2year and 3year formation and testing strategies (t_{1t}: 1.640 and 5.611 respectively, in Panel B). In Panel C, it can be observed that the two-year formation and testing strategies are no longer significantly profitable for the loser portfolio. With respect to the one and three years strategies however, there are some changes regarding in the performance of losers. Losers ACAR's increase from 0.0193 to 0.1017 for the 1year formation and testing strategy. More spectacularly for the 3year formation and testing strategy, loses (-0.4731) turn to profits (0.1672).

It is thus obvious, that when August is excluded, profits are larger in almost all cases, and they are also statistically significant for the loser portfolio in four cases compared to one for the whole sample. The arbitrage profits are also significant in three cases compared to just one for the whole sample.

Table 4.7
Contrarian Profits in the ASE (Excluding August)

	$ACAR_{Wt}$	$ACAR_{Lt}$	$ACAR_{CES}$ (t_{3t})	$ACAR_{Lt}$-$ACAR_{Wt}$ (t_{1t})
			Panel A **Market-adjusted returns [u_i=R_{it}-R_{Mt}]**	
1year testing period	-0.12659	0.1732	0.29979 (1.682)**	0.29979 (1.373)
2year testing period	-0.20268	0.25822	0.46091 (5.177)*	0.46091 (1.204)
3year testing period	0.8798	0.19443	1.07423 (3.611)*	1.07423 (1.942)**
			Panel B **Systematic risk-adjusted returns [e_i=(R_{it}-R_{Ft})-a–β_{it}(R_{Mt}-R_{Ft})]**	
1year testing period	-0.1360	0.22092	0.35691 (1.818)**	0.35691 (1.346)
2year testing period	-0.31451	0.4424	0.75692 (3.810)*	0.75692 (1.640)**
3year testing period	-0.66863	0.76100	1.42963 (6.097)*	1.42963 (5.611)*
			Panel C **Time-varying systematic risk-adjusted returns [Kalman Filter]**	
1year testing period	0.04511	0.10167	0.05656 (0.324)	0.05656 (0.228)
2year testing period	-0.0408	0.20393	0.24473 (0.722)	0.24473 (0.406)
3year testing period	0.10320	0.16724	0.06403 (0.124)	0.06403 (0.148)

Notes to Table 4.7:

t-statistics appear in parenthesis

- * denotes significance at the 5% level
- ** denotes significance at the 10% level

Weekly data, 1989-2001.

As mentioned, this effect is also present for other markets (Draper & Paudyal 1997), but not as severe. The explanation may be that in the Greek economy, there is a standstill during the month of August, given that the vast majority of the population takes its annual leave during August and the middle of the September. There are normally no macroeconomic news during August, and transactions volume falls to very low levels until mid September. Investors go away for holidays and shift to Blue Chip companies for security or even liquidate their contrarian positions until the economy and the market functions normally again in mid to late September. This could be an explanation for losers being affected, while the winner portfolio remains immune to the August effect

4.3.6 Changes in risk between formation and testing Periods

Tables 4.8, 4.9 and 4.10 report the results for estimating equation (4.24) for the 1-year formation and testing strategy, for the winner, loser, and arbitrage portfolio respectively. While Table 4.11 reports the same results for the 2-year formation and testing strategy, and Table 4.12 reports results for the 3-year strategy. All portfolios for all three strategies have a statistically significant mean abnormal return in the formation period: for example the aggregated α_{li} for the 1-year formation and testing strategy in Table 4.8 is 0.0246 (t-statistic: 10.003) for the winner portfolio, -0.0167 (t-statistic: -7.808) for the loser portfolio (Table 4.9), and -0.0413 (t-statistic: -12.864) for the arbitrage portfolio (Table 4.10). The aggregated mean abnormal return of the formation period for the 2-year formation and testing strategy in Table 4.11 is 0.0175 (t-statistic: 5.419) for the winner portfolio, -0.0117 (t-statistic: -3.497) for the loser portfolio, and -0.0292 (t-statistic: -6.847) for the arbitrage portfolio. The aggregated mean abnormal return of the formation period for the 3-year formation and testing strategy in Table 4.12 is 0.1192 (t-statistic: 3.212) for the winner portfolio, -0.0063 (t-statistic: -2.21) for the loser portfolio, and -0.0139 (t-statistic: -3.937) for the arbitrage portfolio.

During the testing period, very few cases experience any abnormal returns significantly different from zero. For example, the aggregated α_{2i} for the 1-year formation and testing strategy in Table 4.8 is -0.00004 (t-statistic: -0.185) for the winner portfolio, 0.0020 (t-statistic: 0.153) for the loser portfolio in Table 4.9, and 0.0020 (t-statistic: 0.659) for the arbitrage portfolio in Table 4.10. The aggregated mean abnormal return in the testing period for the 2-year formation and testing strategy in Table 4.11 is 0.0007 (t-statistic: 0.439) for the winner portfolio, 0.0015 (t-statistic: 0.020) for the loser portfolio, and 0.0009 (t-statistic: 0.241) for the arbitrage portfolio. The aggregated mean abnormal return in the testing period for the 3-year formation and testing strategy in Table 4.12 is -0.0004 (t-statistic: -0.275) for the winner portfolio, 0.0014 (t-statistic: 0.956) for the loser portfolio, and 0.0006 (t-statistic: 1.024) for the arbitrage portfolio. There is clearly no aggregate α_{2i} significant for any of the three strategies that the chapter employs.

There are however some cases where the winner or the loser portfolio make a significant abnormal return in a specific testing period. For example, in Table 4.9, the α_2 for the loser portfolio during 1992-1993 is 0.0177 (t-statistic: 2.972) and for 1998-1999 it is 0.0321 (t-statistic: 3.159), both significant at the 5% level. Nevertheless, for 1995-1996 α_2: is -0.0090 (t-statistic: -1.729) and for 1999-2000 it is -0.0061 (t-statistic: -1.839), both significant at the 10% level. The latter negative returns for the testing period indicate that there is no specific pattern as expected according to the overreaction hypothesis. Furthermore, when it comes to the arbitrage portfolio in Table 4.10, there are only two significant α_2's for the 1-year formation and testing strategy: for 1992-1993 with α_{2i} equal to 0.0175 (t-statistic: 2.187), and 1998-1999 with a value of 0.0235 (t-statistic: 2.055). It is interesting to note however, that for the same testing periods that exhibit an increase in the mean abnormal return, there is no accompanying increase in systematic risk from formation to testing period. The only other case with significant abnormal returns for the arbitrage portfolio during the testing period is in Table 4.12 for the 3-year formation and testing strategy for the period 1996-2000 with a α_{2i} of 0.0164 (t-statistic: 2.370).

As regards risk per se, the first point to note is that the formation period betas of losers are not always smaller than those of winners as suggested by Chan; in fact they are often quite similar. Indeed, the aggregated formation period beta, b_i, for the winner portfolio of the 1-year strategy (Table 4.8) is 0.6197 (t-statistic: 9.745) while that of the loser portfolio (Table 4.9) is 0.6601 (t-statistic: 12.074). For the winner portfolio of the 2-year strategy (Table 4.11) b_i is 0.5148 (t-statistic: 6.994) while that of the loser portfolio is 0.7019 (t-statistic: 10.762). In addition, the aggregated formation period beta, b_i, for the winner portfolio for the 3-year strategy (Table 4.12) is 0.4564 (t-statistic: 5.933) while that of the loser portfolio is 0.4277 (t-statistic: 5.075). All the above, seem to suggest that contrary to Chan's 1988 findings and suggestions, there may not be any significant differences in market capitalisation of winners and losers at the beginning of the formation period.

Investigating the issue of changes in risk between formation and testing period, and their effect for results, focus is given to b_{iD} that represents the change in beta from formation to testing period. If b_{iD} is positive (negative) and significant, then it indicates an increase (decrease) in systematic risk from formation to testing period. For the winner portfolio and the 1-year formation and testing strategy (Table 4.8) b_{iD} is 0.2193 (t-statistic: 2.171) while that of the loser portfolio (Table 4.9) is 0.2018 (t-statistic: 2.266). For the winner portfolio and the 2-year formation and testing strategy (Table 4.11) b_{iD} is 0.3542 (t-statistic: 1.839) while that of the loser portfolio is 0.1154 (t-statistic: 1.025). In addition, the aggregated difference between the formation and testing period beta for the winner portfolio and the 3-year strategy (Table 4.12) is 0.2287 (t-statistic: 1.512) while that of the losers is - 0.0010 (t-statistic: -1.65). It can clearly be seen; that the explanation proposed by Chan does not hold given that for the annual horizon strategies there is an increase in risk on aggregate between formation and testing periods for both winners and losers, and not only for losers as Chan expects. On the other hand, for the 2-year strategy, there is an aggregate increase in risk only for the winner portfolio, and for the 3-year strategy the testing period aggregate risk for losers falls while that of winners does not change significantly. If however, Chan's suggestions were correct, then the changes in betas from formation to testing periods should be positive (negative) and significant for all past losers (winners), which is clearly not the case here.

Looking into individual periodic cases instead of aggregate changes, one can say that in general the differences between the formation and testing period betas are insignificant for the 1-year testing and formation strategy. For the two-year formation and testing strategy, there are increases in risk from formation to testing period for both winners and losers (which is against Chan's suggestion again, given that if they were correct only losers should experience an increase in risk). There are also significant differences in formation and testing period risk when it comes to the 3-year strategy, however, there is again no such pattern like the one suggested by Chan (1988), that is, losers are not more risky than winners are in the testing period compared to the formation period. On average, for any strategy, if there is an increase in testing period risk, both winners and losers experience it. This is because risk change is not a specific characteristic of either losers or winners, but it is a common feature to all the stocks in the sample.

To sum up the results for this subsection, the change in risk between formation and testing periods for both winners and losers, is of the same sign and magnitude, which is inconsistent with the suggestion and findings of Chan (1988), but consistent with De Bondt and Thaler (1987). In addition, the findings are consistent with Balvers, Wu and Gilliland (1999), and agree with Lakonishok, Shleifer & Vishny (1994) who show that the risk differential explanation attempted by Chan does not hold. The conclusion is that changes in risk between formation and testing period do not properly explain results, i.e. losers do not become more risky, and winners do not become less risky. Furthermore, although risk changes through time, Chan suggestion does not hold, perhaps because the change in risk is a continuous process that may not be captured if risk is considered to change once every two years (as in the 1-year formation and testing strategy) or every three years (as in the 3-year strategy). Finally, in combination with the results from the Kalman filter, it can be suggested the taking in to account for continuous changes in risk, is more appropriate, given that (as has been shown) such a consideration reduces profits and their significance substantially.

Table 4.8
Changes in Risk of Winner portfolio
Between Formation and Testing Period
(1-year formation - testing period)

$$R_{it} - R_{Ft} = a_{1i}(1 - D_t) + a_{2i}D_t + b_i(R_{Mt} - R_{Ft}) + b_{iD}(R_{Mt} - R_{Ft})D_t + e_{it}$$

Period	α_{1i}	α_{2i}	b_i	b_{iD}
90-91	0.02106	-0.00134	0.34421	0.27171
	(2.779)*	(-0.179)	(3.322)*	(1.213)
91-92	0.01843	0.00878	0.66982	-0.37874
	(1.733)**	(0.826)	(2.375)*	(-0.985)
92-93	0.01733	0.00019	0.10095	0.60847
	(2.840)*	(0.032)	(0.672)	(2.243)*
93-94	0.03170	-0.0086	1.54305	-0.14368
	(5.381)*	(-1.452)	(7.013)*	(-0.496)
94-95	0.02378	-0.00463	0.21296	0.12964
	(4.320)*	(-0.851)	(1.221)	(0.449)
95-96	0.01505	-0.00724	0.66968	-0.02298
	(2.919)*	(-1.405)	(3.068)*	(-0.069)
96-97	0.01169	0.00349	0.36859	0.34022
	(2.678)*	(0.792)	(1.730)**	(1.438)
97-98	0.01708	0.00314	0.90737	-0.28650
	(3.669)*	(0.678)	(8.329)*	(-2.182)*
98-99	0.03308	0.00863	0.28498	1.11206
	(4.048)*	(1.030)	(2.207)*	(5.0427)*
99-00	0.05688	-0.00191	1.09593	0.56333
	(4.983)*	(-0.125)	(4.504)*	(1.039)
Aggregated	0.02460	-0.00004	0.61975	0.21935
	(10.003)*	(-0.185)	(9.745)*	(2.171)*

Notes to Table 4.8:

t-statistics appear in parenthesis

- * denotes significance at the 5% level
- ** denotes significance at the 10% level

Weekly data, 1989-2001.

Table 4.9
Changes in Risk of Loser Portfolio Between Formation and Testing Period (1-year formation - testing period)

$$R_{it} - R_{Ft} = a_{1i}(1 - D_t) + a_{2i}D_t + b_i(R_{Mt} - R_{Ft}) + b_{iD}(R_{Mt} - R_{Ft})D_t + e_{it}$$

Period	α_{1i}	α_{2i}	b_i	b_{iD}
90-91	-0.01917	-0.00325	0.27746	0.13738
	(-2.057)*	(-0.353)	(2.177)*	(0.499)
91-92	-0.01923	-0.00250	0.42551	0.2635
	(-3.759)*	(-0.489)	(3.135)*	(1.423)
92-93	-0.01747	0.01771	0.46024	0.96390
	(-2.909)*	(2.972)*	(3.112)*	(3.608)*
93-94	-0.01653	0.0020	1.2942	0.06134
	(-2.831)*	(0.339)	(5.933)*	(0.213)
94-95	-0.0136	-0.00046	1.33231	-0.46369
	(-2.431)*	(-0.083)	(7.518)*	(-1.579)
95-96	-0.01430	-0.00897	0.87218	-0.06719
	(-2.756)*	(-1.729)**	(3.970)*	(-0.200)
96-97	-0.02262	-0.00483	0.72065	-0.11221
	(-3.58)*	(-0.757)	(2.338)*	(-0.328)
97-98	-0.02285	-0.00535	0.41662	0.03675
	(-2.888)*	(-0.678)	(2.251)*	(0.165)
98-99	-0.01361	0.03212	0.23794	1.25579
	(-1.373)	(3.159)*	(1.519)	(4.695)*
99-00	-0.00749	-0.0061	0.56832	-0.0576
	(-3.011)*	(-1.839)**	(10.719)*	(-0.487)
Aggregated	-0.01668	0.00203	0.66014	0.20179
	(-7.808)*	(0.153)	(12.074)*	(2.266)*

Notes to Table 4.9:

t-statistics appear in parenthesis

- * denotes significance at the 5% level
- ** denotes significance at the 10% level

Weekly data, 1989-2001.

Table 4.10
Changes in Risk of Arbitrage Portfolio Between Formation and Testing Period (1-year formation - testing period)

$$R_{it} - R_{Ft} = a_{1i}(1 - D_t) + a_{2i}D_t + b_i(R_{Mt} - R_{Ft}) + b_{iD}(R_{Mt} - R_{Ft})D_t + e_{it}$$

Period	a_{1i}	a_{2ii}	b_i	b_{iD}
90-91	-0.04023	-0.00191	-0.06675	-0.13432
	(-3.446)*	(-0.166)	(-0.418)	(-0.389)
91-92	-0.03766	-0.011276	-0.24431	0.64223
	(-3.315)*	(-0.993)	(-0.811)	(1.563)
92-93	-0.03480	0.0175	0.35929	0.35543
	(-4.309)*	(2.187)*	(1.807)**	(0.99)
93-94	-0.04824	0.01064	-0.24885	0.20502
	(-6.469)*	(1.413)	(-0.894)	(0.559)
94-95	-0.03738	0.00418	1.11936	-0.59332
	(-4.450)*	(0.502)	(4.206)*	(-1.345)
95-96	-0.02936	-0.00173	0.2025	-0.04421
	(-4.081)*	(-0.241)	(0.665)	(-0.095)
96-97	-0.03431	-0.00832	0.35206	-0.45243
	(-4.736)*	(-1.138)	(0.996)	(-1.153)
97-98	-0.03993	-0.0085	-0.49075	0.32325
	(-4.804)*	(-1.025)	(-2.524)*	(1.379)
98-99	-0.04669	0.02349	-0.04705	0.14373
	(-4.191)*	(2.055)*	(-0.267)	(0.478)
99-00	-0.06437	-0.00419	-0.52760	-0.62093
	(-5.447)*	(-0.266)	(-2.094)*	(-1.106)
Aggregated	-0.04129	0.00199	0.04079	-0.01755
	(-12.864)*	(0.659)	(0.189)	(0.249)

Notes to Table 4.10:

t-statistics appear in parenthesis

- * denotes significance at the 5% level
- ** denotes significance at the 10% level

Weekly data, 1989-2001.

Table 4.11
Changes in Risk Between Formation and Testing Period
(2-year formation - testing period)

$$R_{it} - R_{Ft} = a_{1i}(1-D_t) + a_{2i}D_t + b_i(R_{Mt} - R_{Ft}) + b_{iD}(R_{Mt} - R_{Ft})D_t + e_{it}$$

Period	α_{1i}	α_{2i}	b_i	b_{iD}
		Panel A		
		Winner Portfolio		
90-93	0.01323	0.00613	0.14506	-0.00079
	(2.381)*	(1.112)	(1.510)	(-0.004)
92-95	0.01932	-0.00552	0.76570	0.28943
	(5.014)*	(-1.422)	(6.835)	(1.618)
94-97	0.01016	-0.00412	0.22500	0.45408
	(2.964)*	(-1.211)	(1.829)**	(2.846)*
96-99	0.01048	0.01013	0.82114	-0.06370
	(3.477)*	(3.307)*	(9.132)*	(-0.604)
98-00	0.0341	-0.00319	0.61709	1.09219
	(5.121)*	(-0.250)	(5.162)*	(2.577)*
Aggregate	0.017458	0.000686	0.51480	0.35424
	(5.419)*	(0.439)	(6.994)*	(1.839)**
		Panel B		
		Loser Portfolio		
90-93	-0.0159	0.00600	0.30656	0.53675
	(-2.996)*	(1.140)	(3.342)*	(3.009)*
92-95	-0.01056	-0.00336	1.16446	-0.14343
	(-2.617)*	(-0.825)	(9.928)*	(-0.766)
94-97	-0.01162	-0.00675	1.03355	-0.33893
	(-2.520)*	(-1.475)	(6.25)*	(-1.580)
96-99	-0.01777	0.01681	0.44900	0.35295
	(-2.749)*	(2.560)*	(2.329)*	(1.562)
98-00	-0.00265	-0.005	0.55601	0.16982
	(-1.35)	(-1.33)	(15.799)*	(1.361)
Aggregate	-0.01170	0.00154	0.70192	0.11543
	(-3.497)*	(0.020)	(10.762)*	(1.025)
		Panel C		
		Arbitrage Portfolio		
90-93	-0.02913	-0.00012	0.1615	0.53754
	(-3.945)*	(-0.017)	(1.265)	(2.166)*
92-95	-0.02988	0.00217	0.39876	-0.43287
	(-5.782)*	(0.416)	(2.654)*	(-1.805)**
94-97	-0.02178	-0.00263	0.80855	-0.79300
	(-3.983)*	(-0.484)	(4.121)*	(-3.117)*
96-99	-0.02825	0.00669	-0.37213	0.41665
	(-4.607)*	(1.073)	(-2.035)*	(1.944)**
98-00	-0.03675	-0.00181	-0.06107	-0.92237
	(-5.635)*	(-0.144)	(-0.522)	(-2.222)*
Aggregate	-0.02916	0.00086	0.18712	-0.23881
	(-6.847)*	(0.241)	(1.568)	(-0.867)

Notes to Table 4.11:

t-statistics appear in parenthesis

- * denotes significance at the 5% level
- ** denotes significance at the 10% level

Weekly data, 1989-2001.

Table 4.12
Changes in Risk Between Formation and Testing Period
(3-year formation - testing period)

$$R_{it} - R_{Ft} = a_{1i}(1 - D_t) + a_{2i}D_t + b_i(R_{Mt} - R_{Ft}) + b_{iD}(R_{Mt} - R_{Ft})D_t + e_{it}$$

Period	α_{1i}	α_{2i}	b_i	b_{iD}
		Panel A		
		Winner Portfolio		
90-95	0.01287	0.0049	0.09836	0.45384
	(3.387)*	(1.295)	(1.363)	(2.923)*
93-98	0.01182	-0.00519	0.58575	-0.04404
	(4.310)*	(-1.887)**	(5.877)*	(-0.378)
96-00	0.01036	-0.0015	0.87122	0.31506
	(3.503)*	(-0.366)	(13.448)*	(2.728)*
Aggregate	0.01192	-0.00043	0.4564	0.22870
	(3.212)*	(-0.275)	(5.933)*	(1.512)
		Panel B		
		Loser Portfolio		
90-95	-0.01194	0.00281	0.45683	0.51946
	(-2.780)*	(0.657)	(5.600)*	(2.961)*
93-98	-0.0077	0.00161	1.15063	-0.94691
	(-2.050)*	(0.427)	(8.431)*	(-5.937)*
96-00	-0.01426	0.01498	0.39853	1.68621
	(-2.871)*	(2.249)*	(3.663)*	(8.69)*
Aggregate	-0.00634	0.00145	0.42769	-0.00100
	(-2.21)*	(0.956)	(5.075)*	(-1.65)**
		Panel C		
		Arbitrage Portfolio		
90-95	-0.02482	-0.00209	0.35847	0.06562
	(-4.424)*	(-0.374)	(3.365)*	(0.286)
93-98	-0.01952	0.00680	0.56487	-0.90287
	(-4.537)*	(1.575)	(3.613)*	(-4.941)*
96-00	-0.02462	0.01643	-0.47269	1.37115
	(-4.764)*	(2.370)*	(-4.175)*	(6.792)*
Aggregate	-0.01395	0.00065	0.26256	-0.16937
	(-3.937)*	(1.024)	(0.804)	(0.613)

Notes to Table 4.12:

t-statistics appear in parenthesis

- * denotes significance at the 5% level
- ** denotes significance at the 10% level

Weekly data, 1989-2001.

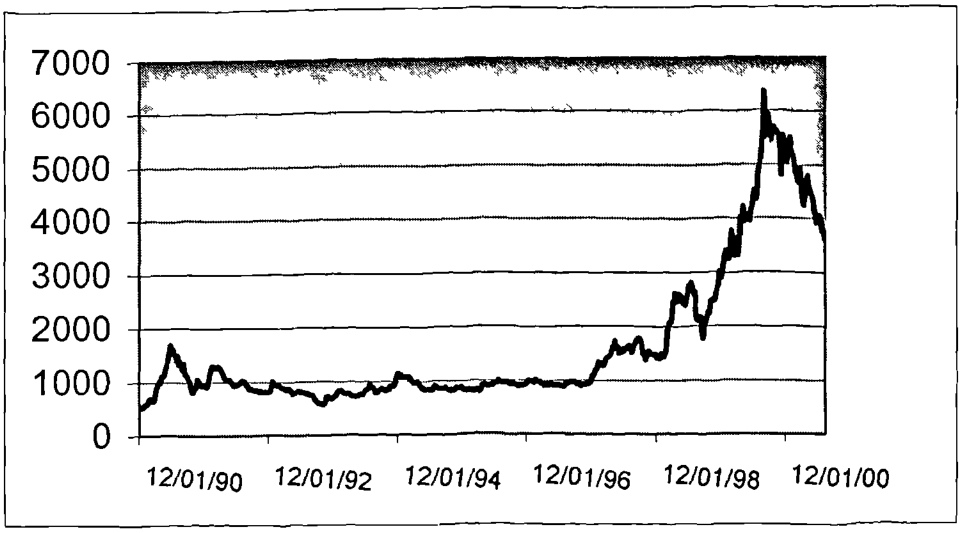
4.3.7 The effect of formation period volatility

One of the main findings of experimental psychology and more specifically of Kahneman and Tversky (1973,1974) is that humans overreact to new information by attaching higher weights to it. A real life example is the recent public killings that took place in the US from the serial sniper. Although the long-term probability of being killed by a serial sniper had not changed, individuals attached more weight in the recent killings, and thought that the probability of being shot in public places was much higher. As a result, they avoided living their premises unless they could not do otherwise. As regards investors, the overreaction hypothesis goes all the way back to Keynes and "animal spirits". Put simply investors don't react to information according to Bayes' rule. More specifically investors also overreact new prices, overweighing them compared to past ones. In recent years, contrarian strategies were formed to take advantage of the above regularity by De Bondt and Thaler (1985) and many others after that. According to De Bondt and Thaler, extreme winners (losers) in one period will become losers (winners) in the next period, because they were winners (losers) due to an initial overreaction that is later corrected. It has been the case according to the empirical finding as we saw in the literature review, that the higher the overshooting is during the formation period, the higher the reversals will be during the testing period. In other words, the higher the extremities in the formation period (i.e. the higher the volatility), the higher the return reversals and the profits in the testing or holding period. In addition, some researchers, for example Bacmann and Dubois (1998), have shown that contrarian strategies are more profitable in bull rather than bear markets. Of course, the above regularities can also be explained by adaptive control processes, which incorporate historical activity in the decision making process of holding the optimal portfolio. Martell and Philippatos (1974) employ two learning models that allow for modifications on the rule, and test whether the martingale hypothesis holds for commodities markets, and combine adaptive filters rules, which should provide a zero return compared to a buy and hold portfolio for martingale processes. According to their findings, this is not the case since returns are higher and less risky compared to buy-and-hold returns, and the validity of the martingale model is questioned. Their model could also be applied in the mean reverting processes that DeBondt and Thaler name overreaction, since the conditions set out by the authors (p.494) for adaptive modeling are satisfied here.

This subsection aims to determine whether higher formation period volatility as measured by standard deviation, can lead to higher return reversals and thus higher contrarian profits in the testing period. Put simply, contrarian profits and reversals under more volatile periods are compared with less volatile periods. If overreaction suggestions are correct, then the higher the market volatility in the formation period, the more extreme the movements in individual stock prices are going to be, and thus higher reversals and contrarian profits should be expected. Testing for the possible relationship of volatility and reversals is also appropriate, given that in contrarian strategies extreme losers and winners are employed (i.e. stocks that are bound to experience higher volatility) to form portfolios. In addition, the subsection seeks an indication on whether contrarian strategies behave differently in bull and bear markets, and does so by repeating comparisons for profitability under bull and bear markets.

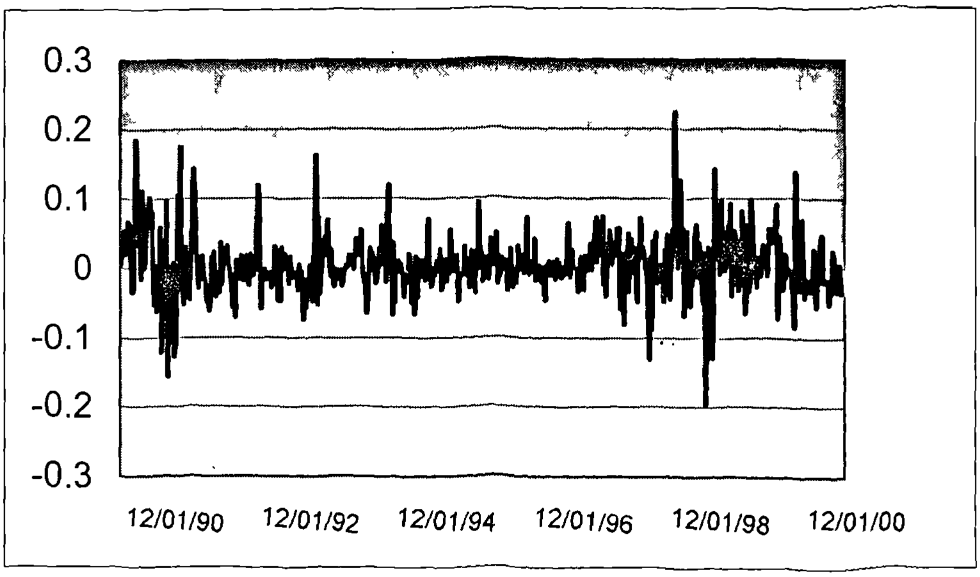
As can be seen in Figure 4.7, the behaviour of the ASE GPI that is used as a proxy for the market portfolio can be segmented into three parts. The first is from 1991 up to the end of 1996, where prices seem to be stable (especially for 1994 to the end of 1996). Then from 1997 to late 1999 there is a bull market with large price increases, and thereafter a large decline in prices.

Figure 4.7
ASE General Price Index 1990-2000



Data Source: Datastream International

Figure 4.8
ASE General Price Index returns 1990-2000



Data Source: Datastream International

Figure 4.8 indicates that in the very early and especially the late part of the sample period there is increased return volatility, while in the years in middle part there is less volatility, which will facilitate the chapter's purposes in this section. The chapter starts by looking into each one of the basic strategies: the one, two and three-year formation and testing strategies; and contrasts their CARs during different market conditions, to verify or discard the expectations mentioned earlier.

Table 4.13
Performance of portfolios and formation Period volatility (3YF3YT)

	Formation Period	**Testing Period**				
	ASE GPI		**Losers**		**Winners**	
Period	S.Dev.	Return's	CAR	All period ACAR	CAR	All period ACAR
first 90-95 F 90-92 T 93-95	243.760	Market adj.	0.444	0.056	0.880	**-0.133**
		CAPM adj.	0.373	0.741	**-0.359**	**-1.108**
		Kalman adj.	0.139	**-0.47**	**-0.831**	**-0.493**
		Ex. January	0.240	0.274	0.749	**-0.088**
		Ex. August	0.563	0.194	0.004	**-0.880**
second 93-98 F 93-95 T 96-98	91.8558	Market adj.	**-0.333**	-||-	**-1.146**	-||-
		CAPM adj.	1.109*	-||-	**-1.855**	-||-
		Kalman adj.	**-1.085**	-||-	**-0.154**	-||-
		Ex. January	0.307*	-||-	**-0.926**	-||-
		Ex. August	**-0.175**	-||-	**-1.764**	-||-
third 96-00 F 96-98 T 99-00	581.070	Market adj.	1.468	-||-	**-0.094**	-||-
		CAPM adj.	1.494	-||-	**-0.496**	-||-
		Kalman adj.	0.949	-||-	0.416	-||-
		Ex. January	1.181	-||-	**-0.234**	-||-
		Ex. August	1.282	-||-	**-0.109**	-||-

Notes to Table 4.13:

* Denotes that although finally positive, the portfolio has -ve returns for most of the period.
ACAR's are the average CAR for all three periods.
Weekly data, 1989-2001.

The cumulative abnormal returns (CARs) and Average cumulative abnormal returns (ACARs) of losers and winners during testing periods for the three years strategy are in Table 4.13. It is clear from the ACARs that the portfolio formed from extreme losers in the past three years (formation period) outperforms prior extreme winners for the next three years (testing period). Not only so, but winners ACARs are negative for all specifications of returns and also when January and August are excluded from the sample. At the same time, past losers become winners in all but one case (where they still however outperform prior winners[75]). Furthermore, when the formation period market volatility (standard deviation) is high (as in: period one: 243.76, and period three: 581.070) then the testing period CARs for losers are positive for all strategies. By further comparing the volatilities of periods one and three, it is clear that the higher the formation period volatility, the higher the profitability[76]. The situation is different however when the formation period volatility is low as in period two (91.856), where most CARs are negative, and even the two that are not, are negative for more than two and a half out of the three years in the testing period.

With respect to the market behaviour, as can be seen for the bear market period between 1990 and the end of 1996 the stocks do both well and bad based on whether the volatility is high or low respectively. However, the extremely good performance of prior losers in the third testing period might also be connected with the presence of bull markets. Nevertheless, one must see what holds for the other two formation and testing strategies before rushing into conclusions.

[75] But the loser ACARs are negative solely due to the bad performance of the second period.
[76] Under the assumption that volatility is one of the main reasons that drives the magnitude of the reversals, and that there is no other underlying factor that does so.

Table 4.14
Performance of portfolios and formation Period volatility (2YF2YT)

	Formation Period	**Testing Period**				
	ASE GPI		**Losers**		**Winners**	
Period	S.Dev.	Return's	CAR	All period ACAR	CAR	All period ACAR
first 90-93 F 90-91 T 92-93	257.121	Market adj.	0.655	0.261	0.808	0.120
		CAPM adj.	0.670	0.370	0.537	**-0.104**
		Kalman adj.	0.393	0.299	**-0.191**	**-0.154**
		Ex. January	0.491	0.305	0.954	0.187
		Ex. August	0.610	0.258	**-0.131**	**-0.203**
second 92-95 F 92-93 T 94-95	91.9863	Market adj.	**-0.357**	-||-	**-0.597**	-||-
		CAPM adj.	**-0.329**	-||-	**-0.939**	-||-
		Kalman adj.	**-0.199**	-||-	**-0.379**	-||-
		Ex. January	**-0.349**	-||-	**-0.431**	-||-
		Ex. August	**-0.187**	-||-	**-0.571**	-||-
third 94-97 F 94-95 T 96-97	83.4246	Market adj.	**-0.783**	-||-	**-0.513**	-||-
		CAPM adj.	**-0.604**	-||-	**-0.602**	-||-
		Kalman adj.	**-1.084**	-||-	**-0.806**	-||-
		Ex. January	**-0.554**	-||-	**-0.260**	-||-
		Ex. August	**-0.550**	-||-	**-0.746**	-||-
Fourth 96-99 F 96-97 T 98-99	305.477	Market adj.	1.528	-||-	0.783	-||-
		CAPM adj.	1.744	-||-	0.586	-||-
		Kalman adj.	2.084	-||-	0.761	-||-
		Ex. January	1.632	-||-	0.486	-||-
		Ex. August	1.160	-||-	0.636	-||-
fifth 98-00 F 98-99 T 00	1356.22	Market adj.	-	-	**-0.446**	-
		CAPM adj.	-	-	**-0.595**	-
		Kalman adj.	-	-	**-0.620**	-
		Ex. January	-	-	**-0.547**	-
		Ex. August	-	-	**-0.322**	-

Notes to Table 4.14:

The fifth period consists only of 2000, and is thus not analysed for past losers, because as we have explained literature has found reversals not to occur in horizons less than a year after formation. See also notes to Table 4.13

Table 4.14 shows that for the two-year strategy, the prior two years' (formation period) losers outperform past winners in terms of ACARs in all cases during the next two years (testing period). Note also, that prior loser (winner) ACARs are all positive (mostly negative), consistent with the overreaction hypothesis. Looking into formation period volatilities, the picture is the same as before, the higher the volatility the better the past losers perform. However, there are no results for the last period, given that it consists of less than a year's observations[77]. The higher the volatility, the better the winners perform as well, but the improvement is smaller than for losers, in which case the contrarian portfolio benefits from the effect of volatility[78]. Furthermore, even when prior losers remain losers, that is, they still have a negative sign for the CARs of a specific period, they outperform past winners most times (loosing less compared to past winners' loses).

Both winners and losers do better in rising markets (see Figure 4.7) as in the fourth period for example (96-99); however, winners become losers in the fifth period[79], which probably shows that the effect of the market price trends, and speed of changes, is asymmetric. Winners do better in rising markets than in falling ones, but losers still outperform winners on average in both situations.

[77] Contrarian strategies need a few months before they start delivering profits. For example Chopra *et al.* (1992) show that they need a year before they deliver profits, Jegadeesh & Titman (1993) find that for the first eight months contrarian strategies do not work. These findings suggest that contrarian strategies start delivering profits at least eight months after the formation period. The fifth sub period we have here is less than eight months after formation, so we should not consider it for past losers.

[78] That is, if losers do better and winners also do better when volatility is higher, but losers' performance improves more than the winners does, then contrarian profits would increase.

[79] Here we consider the evidence, because according to literature winners perform better in the first few months after formation. For example Jegadeesh & Titman (1993) among many others find that for the first eight months winners remain winners and do better than prior losers.

Table 4.15
Performance of portfolios and formation Period volatility (1YF1YT)

	Formation Period	**Testing Period**				
	ASE GPI		**Losers**		**Winners**	
Period	S.Dev.	Return's	CAR	All period ACAR	CAR	All period ACAR
first 90-91 F 90 T 91	333.264	Market adj.	0.023	0.176	0.056	0.046
		CAPM adj.	**-0.157**	0.142	**-0.187**	**-0.028**
		Kalman adj.	**-0.012**	0.019	0.043	0.019
		Ex. January	0.154	0.182	0.139	0.053
		Ex. August	0.041	0.173	**-0.179**	**-0.126**
second 91-92 F 91 T 92	151.357	Market adj.	**-0.024**	-||-	0.699	-||-
		CAPM adj.	**-0.255**	-||-	0.559	-||-
		Kalman adj.	**-0.502**	-||-	0.283	-||-
		Ex. January	**-0.210**	-||-	0.743	-||-
		Ex. August	**-0.057**	-||-	0.185	-||-
third 92-93 F 92 T 93	110.315	Market adj.	0.982	-||-	**-0.031**	-||-
		CAPM adj.	0.605	-||-	0.110	-||-
		Kalman adj.	0.532	-||-	0.171	-||-
		Ex. January	0.856	-||-	0.052	-||-
		Ex. August	0.726	-||-	**-0.028**	-||-
fourth 93-94 F 93 T 94	68.877	Market adj.	0.002	-||-	**-0.564**	-||-
		CAPM adj.	**-0.081**	-||-	**-0.714**	-||-
		Kalman adj.	**-0.185**	-||-	**-0.649**	-||-
		Ex. January	**-0.110**	-||-	**-0.135**	-||-
		Ex. August	**-0.018**	-||-	**-0.565**	-||-
fifth 94-95 F 94 T 95	102.398	Market adj.	**-0.009**	-||-	**-0.165**	-||-
		CAPM adj.	0.124	-||-	**-0.358**	-||-
		Kalman adj.	**-0.450**	-||-	**-0.340**	-||-
		Ex. January	0.113	-||-	**-0.145**	-||-
		Ex. August	0.220	-||-	**-0.168**	-||-

Table continues in next page

Period	Formation Period ASE GPI S.Dev.	Testing Period Return's	Losers CAR	Losers All period ACAR	Winners CAR	Winners All period ACAR
sixth						
95-96		Market adj.	**-0.447**	-||-	**-0.342**	-||-
		CAPM adj.	**-0.376**	-||-	**-0.413**	-||-
F 95	55.210	Kalman adj.	**-0.562**	-||-	**-0.491**	-||-
T 96		Ex. January	**-0.293**	-||-	**-0.480**	-||-
		Ex. August	**-0.338**	-||-	**-0.211**	-||-
seventh						
96-97		Market adj.	**-0.393**	-||-	0.076	-||-
		CAPM adj.	**-0.657**	-||-	**-0.170**	-||-
F 96	36.462	Kalman adj.	**-0.555**	-||-	**-0.118**	-||-
T 97		Ex. January	**-0.270**	-||-	0.093	-||-
		Ex. August	**-0.342**	-||-	**-0.185**	-||-
eight						
97-98		Market adj.	**-0.535**	-||-	**-0.015**	-||-
		CAPM adj.	**-0.378**	-||-	**-0.024**	-||-
F 97	196.625	Kalman adj.	0.042	-||-	0.032	-||-
T 98		Ex. January	**-0.308**	-||-	**-0.092**	-||-
		Ex. August	**-0.449**	-||-	**-0.125**	-||-
ninth						
98-99		Market adj.	1.987	-||-	0.704	-||-
		CAPM adj.	2.454	-||-	0.945	-||-
F 98	441.216	Kalman adj.	1.866	-||-	1.248	-||-
T 99		Ex. January	1.709	-||-	0.301	-||-
		Ex. August	1.778	-||-	0.137	-||-
tenth						
99-00		Market adj.	-	-||-	**-0.379**	-||-
		CAPM adj.	-	-||-	**-1.029**	-||-
F 97	996.915	Kalman adj.	-	-||-	**-1.043**	-||-
T 00		Ex. January	-	-||-	**-0.734**	-||-
		Ex. August	-	-||-	**-0.688**	-||-

Notes to Table 4.15

See also notes to Table 4.13
We exclude the tenth period for losers for the same reasons that we did in the previous Table, and we do not exclude prior winners for the same reasons again as in the previous Table.

Table 4.15 demonstrates that even for the one-year strategy, past losers beat past winners[80] on average, if the strategy is followed for all ten years (this can be seen from ACARs). Note also that although past losers have a positive sign in all their ACARs as before, past winners have a negative sign in only two of them compared to past strategies where they had more. Results are not very clear however when looking into the CAR's of each year. It is anticipated however -given past evidence- that contrarian strategies will not do as well for the one year strategies as for longer ones, since it takes time for losers to become winners, and winners remain so for a period before becoming losers. However, when excluding January, both losers and winners do better, except for bull markets, where they are both better of when January is included in the sample.

Summing up for all three strategies, prior losers outperform prior winners in all cases if the strategy is followed for the whole sample period (that can be seen by looking in the ACARs). As regards individual years (CARs), contrarian strategies perform better when formation period volatility is higher, since the effect of volatility is asymmetric and is stronger for losers than for winners. Contrarian strategies perform better when longer investment horizons are considered, and using a one-year horizon could be avoided unless volatility has been high in the formation period and at the same time bull markets are expected in the testing period. A further example of how the formation period length also affects the profitability of the strategy[81] follows next.

[80] Except for when using the Kalman filter returns, where they do equally well.

[81] We say here a further example, because by observing the graphs for the three years formation and testing strategy or the two years formation and testing strategy, and by looking at a shorter holding period each time (i.e. reading the graph for up to one year or two years each time for the

Table 4.16 looks into Market and CAPM adjusted returns for one-year formation and three-year testing strategies, to compare them with the values received earlier for the three-year formation and testing strategy. Although formation periods are different in Table 4.16 from Table 4.13, the volatilities are not very different, allowing to test whether it makes a difference when using the previous years winners and losers as opposed to using the past three years ones to construct portfolios.

Table 4.16
Performance of portfolios and formation Period volatility (1YF3YT)

Period	Formation Period ASE GPI S.Dev.	Testing Period Return's	Losers CAR	Losers All period ACAR	Winners CAR	Winners All period ACAR
first 90-93 F 99 T 91-93	333.264	Market adj.	0.215	0.177	0.148	-0.067
		CAPM adj.	0.021	0.347	-0.411	-0.282
second 94-97 F 94 T 95-97	102.398	Market adj.	-0.352	-‖-	-1.375	-‖-
		CAPM adj.	-0.256	-‖-	-1.759	-‖-
third 98-00 F 98 T 99-00	441.216	Market adj.	0.669	-‖-	1.025	-‖-
		CAPM adj.	1.275	-‖-	1.324	-‖-

Notes to Table 4.16:

See notes to Table 4.13

three year formation and testing strategy), we can have a good picture of how using longer formation and shorter holding periods alter our results.

As can be seen by looking at ACARs, if the strategy is performed for the whole sample period profits are as before. For example, the loser ACARs are positive, while the former winners ACARs are negative. In addition, as before, CARs indicate that losers outperform winners for the individual periods as well, and the higher the volatility the better the performance is[82]. The profits are however smaller in magnitude for both winners and losers when compared to three years testing and formation profits. The same pattern also holds for one-year formation and two years testing strategies.

To sum up all results in this subsection, losers outperform winners for all possible strategies attempted and for all return specifications, when these strategies cover the whole sample period (as can be seen by looking in the ACAR values). As regards individual segments of the full sample-period (as can be seen by looking in the CAR values), again losers outperform winners in most cases. Both losers and winners do better under higher formation period volatility, the effect is however asymmetric and favours losers. Both losers and winners do better in bull markets in the testing period, with an asymmetry again favouring losers. When there is a downturn in the market, prior winners do extremely bad, since they are stocks that exhibit positive serial correlation for long periods, and thus when they become losers they tend to build a momentum (as they did of course when they were winners).

[82] Looking at Table 4.15 for the third period, it can be seen that the chapter's earlier suggestion for the need of more than a year's data in the testing period before one considers loser performance, is correct. This is obvious if one compares the final period of Table 4.16 with Table 4.15. In Table 4.16 there is enough data for the volatility effect to be observed, which is not the case for Table 4.15, where although volatility is high in the formation period, the testing period is short and does not allow the reversals in loser performance. This is therefore further evidence supporting the chapter in not considering the results for the losers in the last period of Table 4.15.

4.4 Conclusion

This chapter documents the profitability of long-term contrarian investment strategies for the ASE by creating portfolios based on the expectations of the overreaction hypothesis. Four different types of returns are employed: market adjusted returns, risk adjusted returns, time-varying risk adjusted returns, and returns in excess of the risk free rate[83], aiming to determine the effect of risk on contrarian profits. The well-documented January effect is also considered. Furthermore, Chan's (1988) methodology is employed as an additional way of accounting for nonstationarity of expected returns. The effect of volatility and the markets behaviour are also examined. One of the innovations of the chapter is the use of the Kalman filter for the first time in such tests. All the above are applied using different time strategies to document the effect of shorter and longer time investment horizons.

Results illustrate that for market-adjusted returns and above the risk free rate returns, profits follow the pattern suggested by the overreaction hypothesis. That is, they are negative for past winners, positive for past losers and for zero investment contrarian portfolios that go long in losers and short in winners; they are however statistically insignificant in most cases. When however risk adjusted (CAPM) returns are used, contrarian profits become significant and increase in magnitude, consistent with the De Bondt and Thaler's (1985) suggestion that losers not only outperform winners but they are also less risky. Profits however tumble in most cases when the unrealistic assumption of constant risk is dropped, and time variation in risk is considered by means of the Kalman filter algorithm. Consistent with Ball and Kothari's (1989) suggestion (that most of the negative serial correlation that leads to contrarian profits is due to time variation in risk), when beta is allowed to change most of the abnormal returns vanish. This has very important implications for all previous tests on the overreaction hypothesis: if it is correct then most of the previous studies findings indicating risk-free overreaction profits might just be an artefact of the lack of proper adjustment for variation in risk and expected returns.

Although the findings agree with Chan's (1988) suggestion regarding time variation in risk, the chapter shows that Chan's methodology for accounting for time variation is inappropriate and unrealistic. Both losers and winners experience on average an increase when moving from testing to formation period consistent with the findings of De Bondt and Thaler (1987), Lakonishok, Shleifer & Vishny (1994), Dissanaike (1997), and others.

The January effect does not explain results; albeit some significant profits (even when using Kalman filter generated returns) when January is excluded. There is however an August effect, that leads to a significant sharp drop in contrarian profits. A possible explanation for this effect could be the very low ASE trading volumes during August, due to the fact that most investors in Greece take their vacation during this month and seek security by shifting their holdings in to blue chips, or liquidating their long contrarian positions, until they return. When August is removed from the sample the problem is rectified.

[83] Which however are not different in behaviour to the market adjusted returns as can be seen in figures 4.18 to 4.20, and Table 4.24 in the Appendix, and are thus not analysed.

It overall appears that, how stock returns are defined is very important for the examination of the profitability of contrarian strategies. This is consistent with the findings of Chopra et al. (1992). Another important finding is that the length of formation periods affects results, and the longer the formation (and holding) period, the higher the profits, consistent with De Bondt and Thaler (1985,1987). For example, a three-year horizon strategy outperforms both a one and two year horizon up to the second year (i.e. holding a three years formation portfolio for two years, outperforms two single one-year strategies).

Losers outperform winners for all strategies apart for the one-year formation and testing strategies for Kalman filter adjusted returns (Figure 4.23). In two more cases, they do equally well, and in the rest, the losers outperform prior winners by anything between 12% and 180% for the three years formation and testing strategy with risk adjusted returns (Figure 4.14). The difference in returns is on average above 20-25%, and supports the overreaction hypothesis.

Put simply, the chapter's strategies deliver profits when followed for the full sample period (1990-2000, based on ACARs), no matter if the intermediate time horizons are one, two, or three years. Profits are possible even if one wants to invest for less than the full period, provided there is high volatility in the formation period, which will guarantee higher profits especially for the two and three years formation and testing strategies.

One of the implications of our findings for investors in the ASE is the ability to make abnormal profits by forming contrarian portfolios based on the performance of the previous three years, and holding them for the next one, two or three years. This can deliver abnormal profits (even when taking in to account for risk) of up to, or above 100% for that year. If investors however hold the stocks for longer than a year, they can make even higher returns. However, they could benefit from liquidating their long positions in August to avoid the August effect discussed, and re-enter the market by the second half of the following calendar month, provided that the benefits from such an action are higher than the costs caused by the increased transaction costs. For one of the strategies proposed in this chapter (forming stocks based on the previous three years and holding them for the next year), there are extremely high profits to be made even if continuous time variation in betas is considered (using the Kalman filter). Using contrarian investment strategies in ASE when there is higher formation period volatility amplifies results. Of course, as already mentioned, given that emerging capital markets like the ASE suffer from thin trading, low liquidity, possibly less informed and rational investors, one would expect predictability (Hong et al. 2000, Kang et al. 2000, Antoniou et al 1997). For example emerging market investors may place too much faith in their own forecasts, biasing their actions (Dabbs et al. 1990). In addition, they may not respond instantaneously to information (Schatzberg and Reiber 1992), and wait to see how informed market participants behave, because either their information is not reliable or they do not have the resources to fully analyse the information. Some of the aforementioned problems will be dealt with in the next chapter, but for the moment, results should thus be viewed under this light.

Transaction costs are very small, and should not be considered, since there is just one set of transactions at the beginning of the strategy and another set at the end of one or two or three years later, depending on the adopted horizon. Remember also that a very small number of stocks (five) is considered in each position. Thus, the profits from strategies suggested in the above paragraph are real profits and exist not only after risk and changes in risk have been accounted, but also after transaction costs.

With regards to the implications for financial theory, it seems that returns are predictable, and the predictability is free of risk, seasonality, and the bid-ask bias (as explained in chapter 3). However, given the effect of time variation in risk as the chapter has shown, it is recommended that other tests for the overreaction hypothesis that have been performed in the past, are repeated using Kalman filter time-varying risk adjusted returns, in order to measure the presence and the magnitude of the bias of their earlier results.

The results also indirectly imply that the adoption of rules (by regulators) that minimize predictability could assist the effort to keep markets efficient, especially following periods of high volatility. Examples of such rules could be the release of company accounting figures more often, or that firms are called to publicly verify or deny rumours that cause overreaction, and to properly quantify misjudged news that have distorted the intrinsic value of their stock (as this is considered to be by the existing models and theories).

Having seen that there is return predictability and profits for long run contrarian strategies, it would be interesting to test whether this is the case for shorter term ones. In addition, although overreaction is the main suggestion for contrarian profits until 1990, this is not the case nowadays. Lo and MacKinley (1990) suggest that contrarian profits are mostly due to underreaction of stock prices to news, and in 1995 Jegadeesh and Titman improve the Lo and Mackinley methodology. More specifically Jegadeesh and Titman propose a way of rectifying a technical error of Lo and Mackinley's methodology, and show that although part of profits could also be related to underreaction to common news, most of them are due to firm specific overreaction. As a next step in research, the thesis does not only examine the effect of using shorter-term contrarian strategies, but also looks into the above discussion and the contribution of both over- and underreaction of market wide and firm specific factors to contrarian profits. This will help to understand the complete mechanics of contrarian strategies under both longer and shorter-term investment strategies and the real reasons behind profitability.

4.5 Appendix

Table 4.17
Descriptive statistics of excess returns of GMM-test portfolios

Portfolio	Mean	St. Error	Skewness	Kurtosis	Jarque-Bera
Banks	0.00199	0.05029	0.34551	1.70649	77.96 (0.00)
Industrials	0.00069	0.04897	0.66602	3.89281	389.35 (0.00)
Insurance	0.00300	0.07163	0.31251	2.81461	191.19 (0.00)
Tobacco	0.00319	0.07598	6.86267	78.2922	145315 (0.00)
Construction	0.00045	0.05353	0.95343	5.51678	783.63 (0.00)
Big	-0.00060	0.04024	0.23264	2.26888	122.93 (0.00)
Large	0.00090	0.04210	0.46145	4.59925	504.27 (0.00)
Medium	0.00175	0.03974	0.23998	4.25980	421.12 (0.00)
Small	0.00145	0.04113	0.41080	2.71167	183.97 (0.00)
ASE GPI	0.00067	0.04386	0.45909	3.47616	297.31 (0.00)

Table 4.18
Sample statistics of Winner (W) and Loser (L) Portfolio
(Systematic risk-adjusted returns, 1-year formation & testing periods)

Period	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A							
Sample statistics of Winner (W) portfolio using Systematic risk-adjusted returns[CAPM]							
90-91	-0.00361	0.023435	-0.056	0.073896	0.1233	1.41461	4.46755
91-92	0.010756	0.064119	-0.18027	0.199298	-0.31614	2.54038	14.84879
92-93	0.002117	0.029246	-0.07999	0.062346	-0.47331	1.10427	4.58355
93-94	-0.01373	0.046904	-0.15404	0.139181	-0.08927	3.33891	24.22375
94-95	-0.00689	0.023463	-0.05857	0.037475	-0.17959	-0.85307	1.85627
95-96	-0.00795	0.030384	-0.07002	0.08169	0.66393	0.75947	5.07005
96-97	-0.00327	0.025713	-0.06853	0.057051	0.2231	-0.04154	0.43509
97-98	-0.00047	0.032787	-0.07611	0.109668	0.57475	2.15789	12.95198
98-99	0.018164	0.058532	-0.17244	0.129653	-0.54329	1.33959	6.44615
99-00	-0.03026	0.067095	-0.14692	0.132468	0.59444	0.19374	2.05554
Panel B							
Sample statistics of Loser (L) portfolio using Systematic risk-adjusted returns[CAPM]							
90-91	-0.00301	0.030429	-0.08907	0.064533	-0.0422	0.56587	0.70922
91-92	-0.0049	0.047884	-0.14444	0.156732	0.86796	3.60396	34.67093
92-93	0.011636	0.030366	-0.06155	0.089709	0.21459	0.26376	0.54982
93-94	-0.00156	0.036032	-0.05866	0.130913	0.96158	2.4354	20.86434
94-95	0.002391	0.03615	-0.08531	0.109078	0.56253	1.01486	4.97402
95-96	-0.00723	0.034936	-0.11862	0.075958	-0.59227	1.93982	11.19306
96-97	-0.01264	0.04283	-0.10385	0.059596	-0.40879	-0.57325	2.16031
97-98	-0.00726	0.051351	-0.12255	0.159379	0.46079	1.19329	4.92538
98-99	0.047196	0.096356	-0.2487	0.230615	-0.64694	0.64094	4.51738
99-00	-0.00048	0.01133	-0.02567	0.019647	-0.42334	-0.5153	1.39171

Table 4.19
Sample statistics of Winner (W) and Loser (L) Portfolio
(Systematic risk-adjusted returns, 2-year formation & testing periods)

Period	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A							
Sample statistics of Winner (W) portfolio using Systematic risk-adjusted returns[CAPM]							
90-91	0.005169	0.028849	-0.04436	0.139169	2.16717	7.09789	299.7221
91-92	-0.00903	0.032089	-0.11636	0.105059	0.2916	2.42875	27.0355
92-93	-0.00579	0.032648	-0.09129	0.098036	0.44752	0.96868	7.53756
93-94	0.00563	0.032024	-0.09344	0.08431	0.03019	0.50999	1.14285
94-95	-0.01749	0.044685	-0.09131	0.085948	0.65305	0.06691	2.42305
Panel B							
Sample statistics of Loser (L) portfolio using Systematic risk-adjusted returns[CAPM]							
90-91	0.006445	0.036708	-0.07257	0.120155	0.72528	0.74449	11.51963
91-92	-0.00316	0.03324	-0.10451	0.120292	0.50281	2.12606	23.96938
92-93	-0.00581	0.031548	-0.06784	0.103188	0.54731	0.40743	5.91146
93-94	0.01677	0.078457	-0.23119	0.211275	-0.07946	0.73322	2.43911
94-95	0.000123	0.013975	-0.02356	0.033895	0.2953	-0.43487	0.76207

Table 4.20
Sample statistics of Winner (W) and Loser (L) Portfolio
(Systematic risk-adjusted returns, 3-year formation & testing periods)

Period	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A							
Sample statistics of Winner (W) portfolio using Systematic risk-adjusted returns[CAPM]							
90-91	-0.0023	0.02486	-0.10722	0.075308	-0.21716	2.0292	27.99084
91-92	-0.0119	0.03921	-0.14133	0.101943	0.24386	0.62199	4.06088
92-93	-0.0058	0.04617	-0.30963	0.082061	-3.92093	24.03802	2290.901
Panel B							
Sample statistics of Loser (L) portfolio using Systematic risk-adjusted returns[CAPM]							
90-91	0.002397	0.040158	-0.11018	0.128601	0.45812	0.76808	9.29144
91-92	0.007108	0.039565	-0.12212	0.13743	0.52686	1.04341	14.29363
92-93	0.017377	0.099647	-0.28187	0.262929	-0.04299	0.2285	0.21358

Table 4.21
Sample statistics of Winner (W) and Loser (L) Portfolio
(Time-varying risk-adjusted returns, 1-year formation & testing periods)

Period	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A							
Sample statistics of Winner (W) portfolio using Time-varying systematic risk-adjusted returns [Kalman Filter]							
90-91	0.000825	0.030029	-0.08632	0.055949	-0.51193	0.82845	3.75832
91-92	0.005451	0.048815	-0.09274	0.192434	1.89152	5.57883	98.44192
92-93	0.003299	0.045582	-0.10828	0.118307	-0.02489	1.14171	2.82964
93-94	-0.01249	0.038206	-0.10158	0.080269	0.12095	0.28642	0.30452
94-95	-0.00655	0.021649	-0.06083	0.03701	-0.18467	-0.27185	0.45568
95-96	-0.00945	0.036652	-0.07842	0.080181	0.64448	0.08904	3.6169
96-97	-0.00227	0.025682	-0.06713	0.058976	0.23615	-0.02034	0.48422
97-98	0.00061	0.031313	-0.07361	0.114663	0.95115	3.02098	27.61428
98-99	0.024006	0.071319	-0.19531	0.179722	-0.51631	0.9705	4.35104
99-00	-0.03066	0.073507	-0.17675	0.146329	0.42664	-0.01592	1.03182
Panel B							
Sample statistics of Loser (L) portfolio using Time-varying systematic risk-adjusted returns [Kalman Filter]							
90-91	-0.00023	0.037339	-0.08826	0.133924	1.03389	3.13257	30.52555
91-92	-0.00965	0.020638	-0.04686	0.051994	0.59369	0.84011	4.58392
92-93	0.010221	0.028955	-0.03909	0.09245	0.4374	-0.05108	1.66374
93-94	-0.00356	0.016948	-0.03479	0.047183	0.42092	0.55944	2.21363
94-95	-0.00865	0.044282	-0.27704	0.082698	-4.23406	27.18807	1756.951
95-96	-0.0108	0.028001	-0.08581	0.04282	-0.34087	0.31082	1.2163
96-97	-0.01068	0.032775	-0.08309	0.074518	0.15965	0.1933	0.30184
97-98	0.000802	0.049187	-0.10241	0.192434	1.14408	3.49171	37.76012
98-99	0.035882	0.083732	-0.1802	0.208377	-0.26151	-0.09162	0.61086
99-00	-0.00488	0.013961	-0.02772	0.026041	0.39673	-0.30325	1.02218

Table 4.22
Sample statistics of Winner (W) and Loser (L) Portfolio
(Time-varying risk-adjusted returns, 2-year formation & testing periods)

Period	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A							
Sample statistics of Winner (W) portfolio using Time-varying systematic risk-adjusted returns [Kalman Filter]							
90-91	-0.0018	0.026611	-0.08008	0.14599	2.20365	11.56131	663.382
91-92	-0.0036	0.036371	-0.10801	0.090172	-0.1099	1.19061	6.35213
92-93	-0.0077	0.038084	-0.07871	0.098326	0.44778	-0.18811	3.62882
93-94	0.0073	0.034037	-0.1002	0.083425	-0.21664	0.46886	1.7661
94-95	-0.0183	0.044997	-0.09355	0.086817	0.64255	0.09163	2.35151
Panel B							
Sample statistics of Loser (L) portfolio using Time-varying systematic risk-adjusted returns [Kalman Filter]							
90-91	0.003781	0.03379	-0.09517	0.114973	0.28457	1.43251	10.29604
91-92	-0.00191	0.028116	-0.08186	0.119845	0.98976	3.39249	66.85248
92-93	-0.01042	0.031479	-0.09019	0.076912	0.28181	0.03097	1.38071
93-94	0.020041	0.07253	-0.1779	0.208785	0.37403	0.3257	2.88457
94-95	-0.00447	0.015541	-0.0358	0.023701	-0.05037	-0.66991	0.65014
	0.003781	0.03379	-0.09517	0.114973	0.28457	1.43251	10.29604

Table 4.23
Sample statistics of Winner (W) and Loser (L) Portfolio
(Time-varying risk-adjusted returns, 3-year formation & testing periods)

Period	Mean	Std Error	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera
Panel A							
Sample statistics of Winner (W) portfolio using Time-varying systematic risk-adjusted returns [Kalman Filter]							
90-91	-0.00533	0.026588	-0.09097	0.057893	-0.03146	0.56962	2.13473
91-92	-0.00099	0.045781	-0.11419	0.134024	0.35453	0.06951	3.2993
92-93	0.004836	0.053341	-0.12431	0.185835	0.54153	1.15488	8.98265
Panel B							
Sample statistics of Loser (L) portfolio using Time-varying systematic risk-adjusted returns [Kalman Filter]							
90-91	0.000888	0.033412	-0.10934	0.141682	0.58788	3.21097	76.00265
91-92	-0.00695	0.026478	-0.0916	0.100799	0.32764	1.92495	26.87645
92-93	0.011029	0.08627	-0.26763	0.197757	-0.16562	0.3194	0.75872

Table 4.24
Contrarian Profits in the ASE

	$ACAR_{Wt}$	$ACAR_{Lt}$	$ACAR_{CES}$ (t_{3t})	$ACAR_{Lt}$-$ACAR_{Wt}$ (t_{1t})
		Panel A Market-adjusted returns $[u_i=R_{it}-R_{Mt}]$		
1year formation and 2year testing period	-0.13341	-0.09911	0.03430 (0.198)	0.03430 (0.148)
1year formation and 3year testing period	-0.06723	0.17727	0.24451 (0.599)	0.24451 (0.321)
		Panel B Systematic risk-adjusted returns $[e_i=(R_{it}-R_{Ft})-a-\beta_{it}(R_{Mt}-R_{Ft})]$		
1year formation and 2year testing period	-0.48171	-0.28471	0.19699 (1.613)	0.19699 (1.016)
1year formation and 3year testing period	-0.28203	0.34701	0.62905 (1.371)	0.62905 (0.623)
		Panel C Returns above the Risk free rate $[u_i=R_{it}-R_{Ft}]$		
1year testing period	0.09548	0.22528	0.12980 (0.624)	0.12980 (0.360)
2year testing period	0.31272	0.45326	0.14054 (0.792)	0.14054 (0.183)
3year testing period	0.10236	0.29114	0.18879 (0.524)	0.18879 (0.620)

Notes to Table 4.24:

t-statistics appear in parenthesis

Here we see results for Market adjusted returns (Panel A) and CAPM adjusted returns (Panel B) using different time horizons, and we also see the results for returns above the risk free rate. Results in the first two cases do not appear to have statistically significant differences, and that is why we do not report any more results in subsection 4.3.3 relevant to the one-year formation and two years testing strategy, and the one-year formation and three years testing strategy. It appears here that the longer the testing period the better the results. However the same holds for the other extreme, since the two negative values for prior losers for the one-year formation and two years testing periods come about in the last 5 months of the holding period. In other words if the holding period is up to a year or longer than two years the strategy seems to work. But for the medium term it does not work, consistent with the findings of the literature. With respect to above Risk-free rate returns, it can be seen that compared to the results in the main text Tables on Market adjusted returns, they are not different. Losers outperform prior winners, however winners have positive average cumulative abnormal returns. The contrarian portfolio profitability is not significant for the full period tested here, but if the portfolio was held for less, then it can deliver significant profits.

Figure 4.9
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 1-year formation & testing periods)

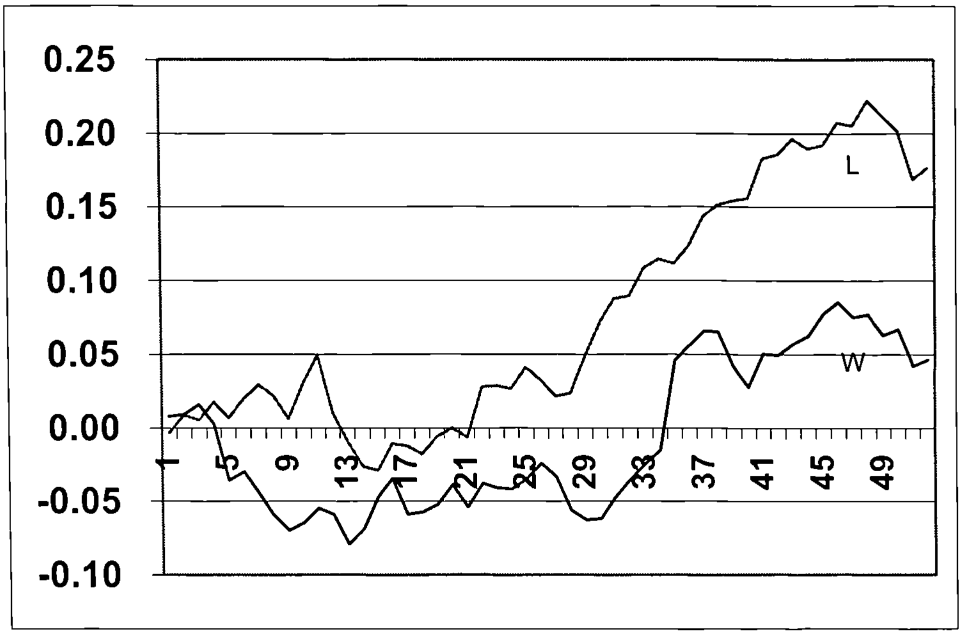


Figure 4.10
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 1-year formation & testing periods)

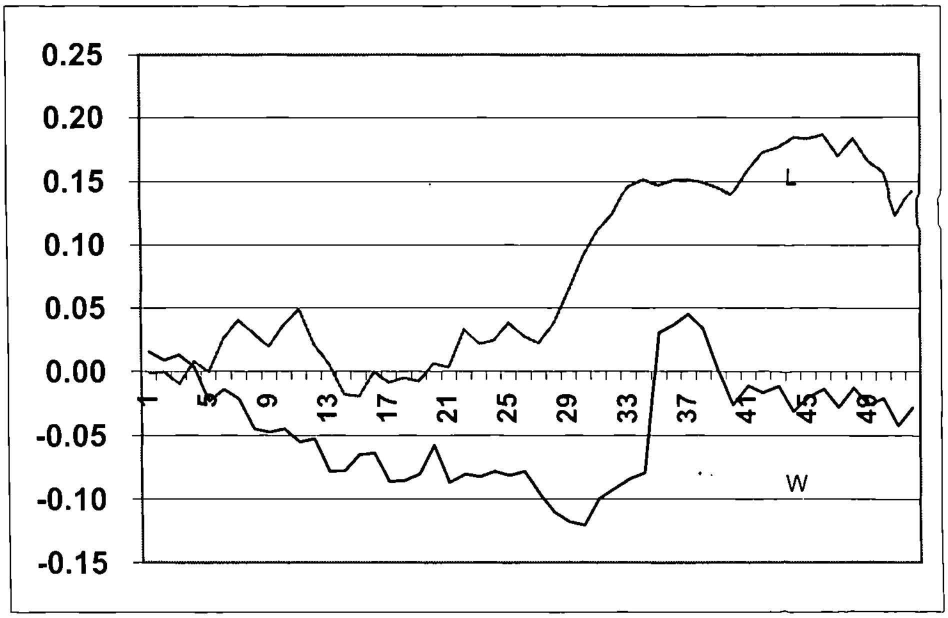


Figure 4.11
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 1-year formation & testing periods)

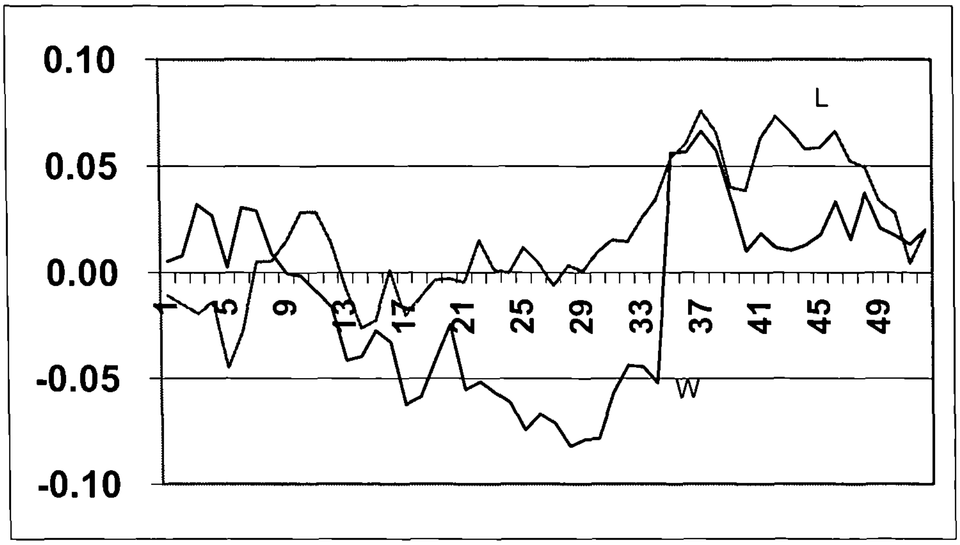


Figure 4.12
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 2-year formation & testing periods)

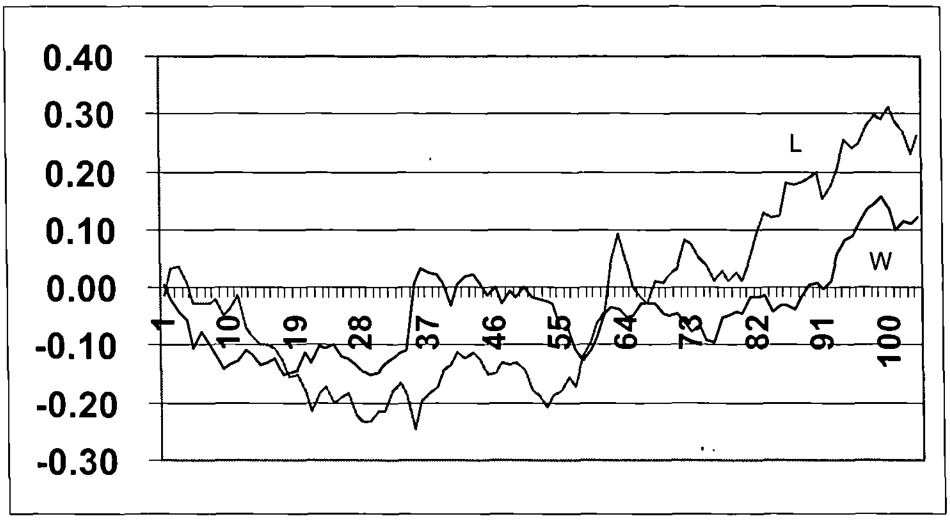


Figure 4.13
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 2-year formation & testing periods)

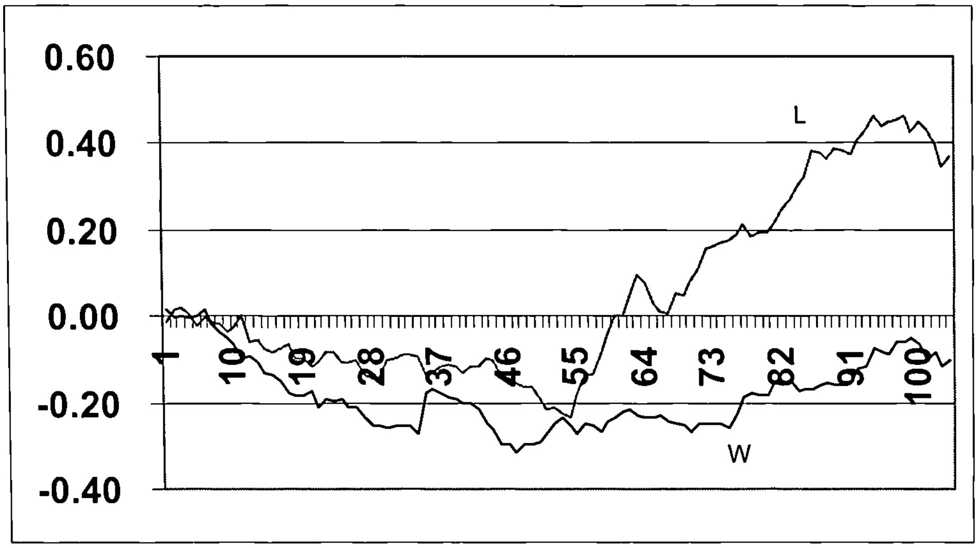


Figure 4.14
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 2-year formation & testing periods)

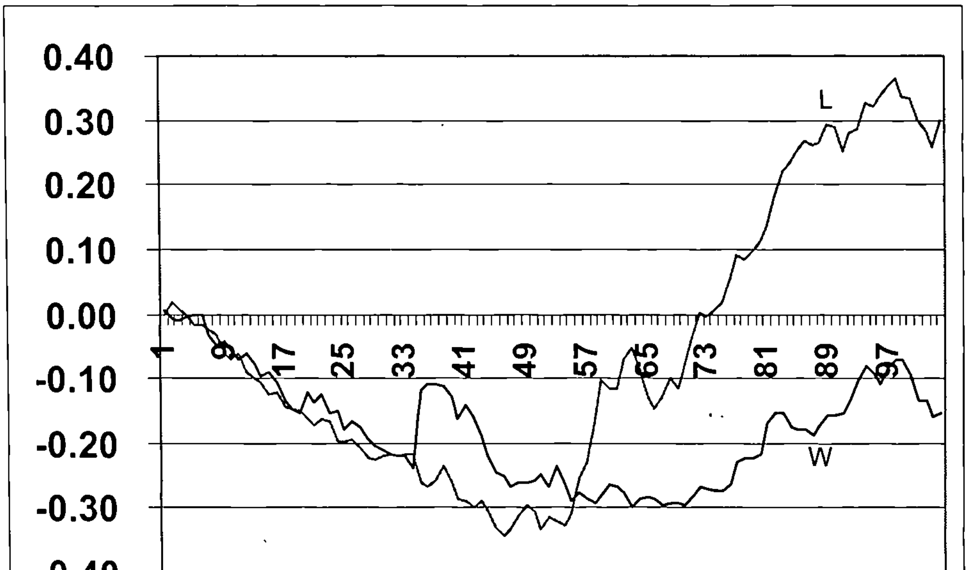


Figure 4.15
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 3-year formation & testing periods)

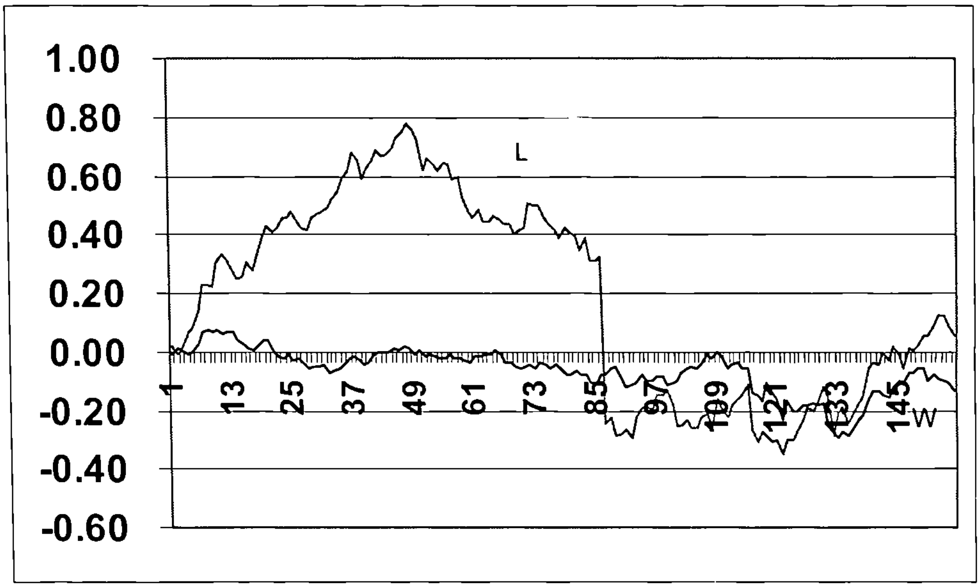


Figure 4.16
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 3-year formation & testing periods)

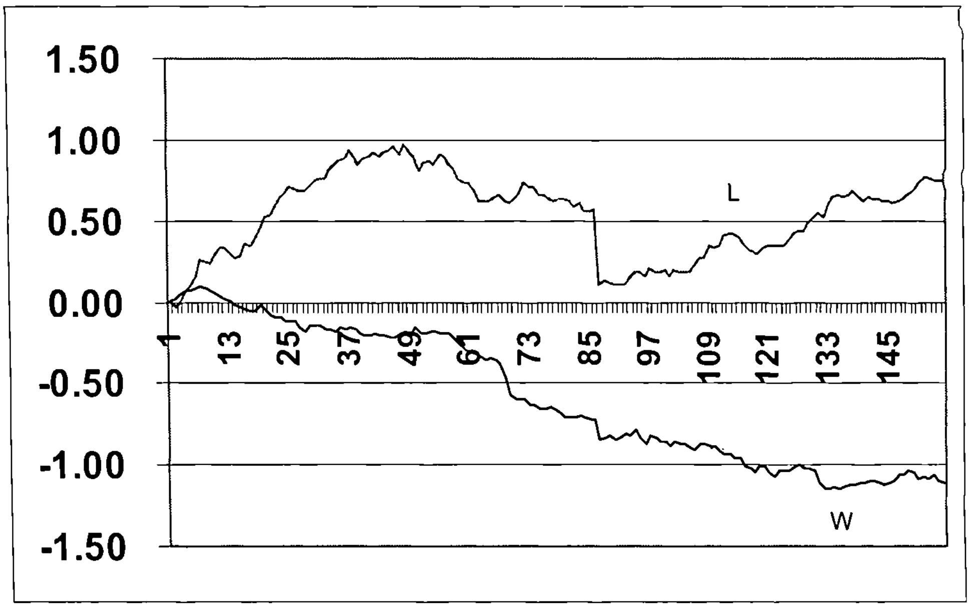


Figure 4.17
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 3-year formation & testing periods)

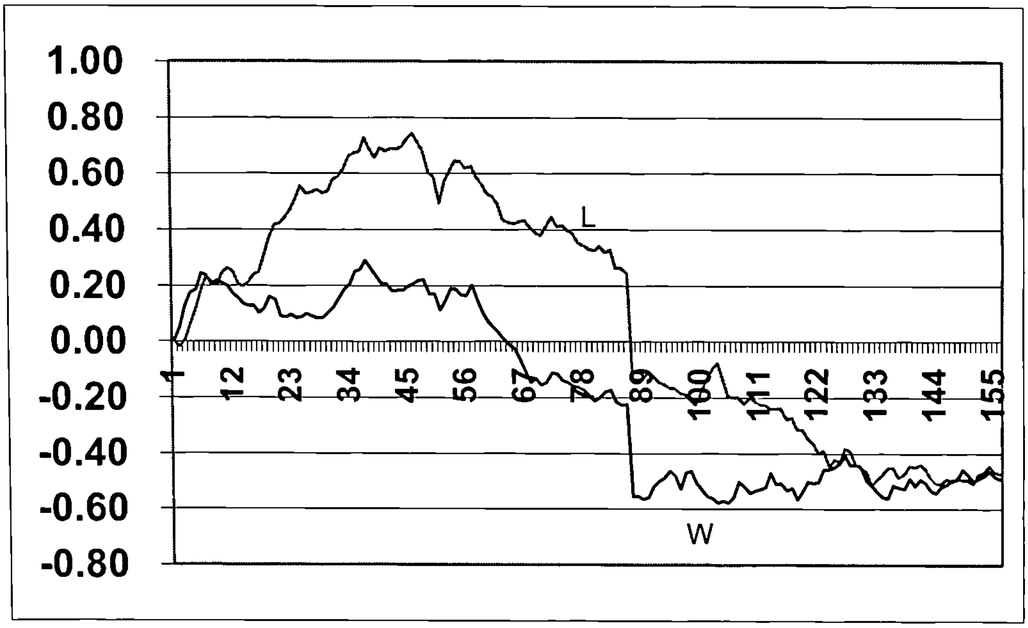


Figure 4.18
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 1-year formation and 2-year testing periods)

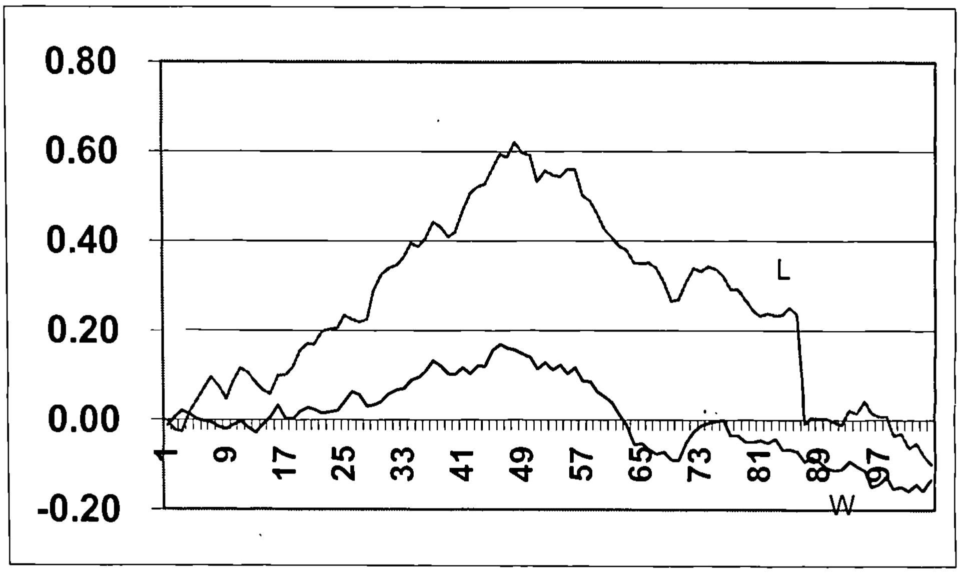


Figure 4.19
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 1-year formation and 3-year testing periods)

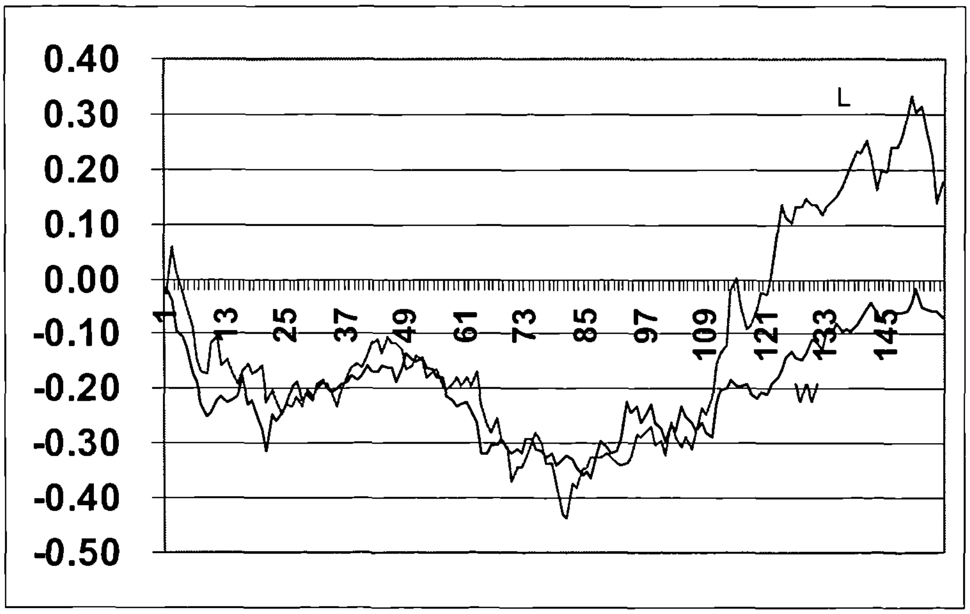


Figure 4.20
ACARs of Winner (W) and Loser (L) Portfolio
(Above Risk Free Rate returns, 1-year formation & testing periods)

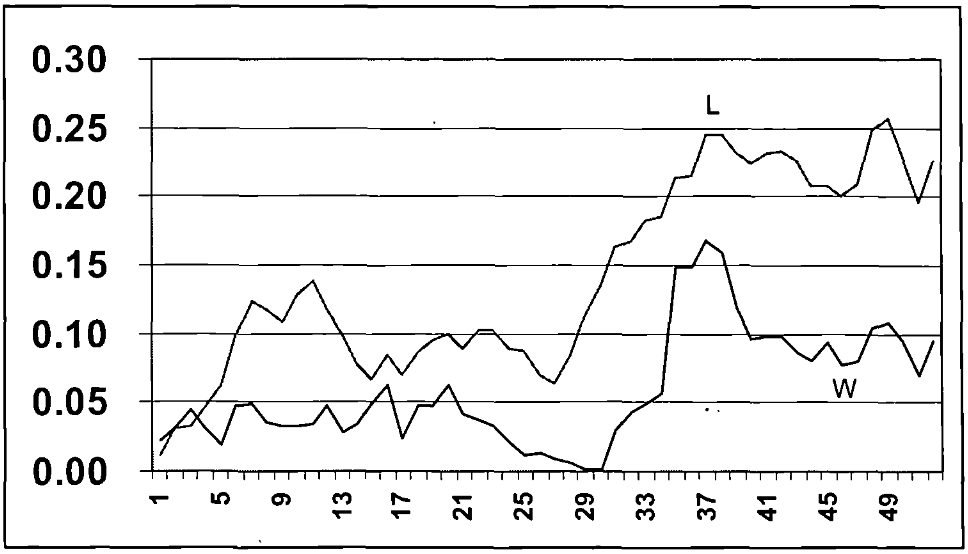


Figure 4.21
ACARs of Winner (W) and Loser (L) Portfolio
(Above Risk Free Rate returns, 2-year formation & testing periods)

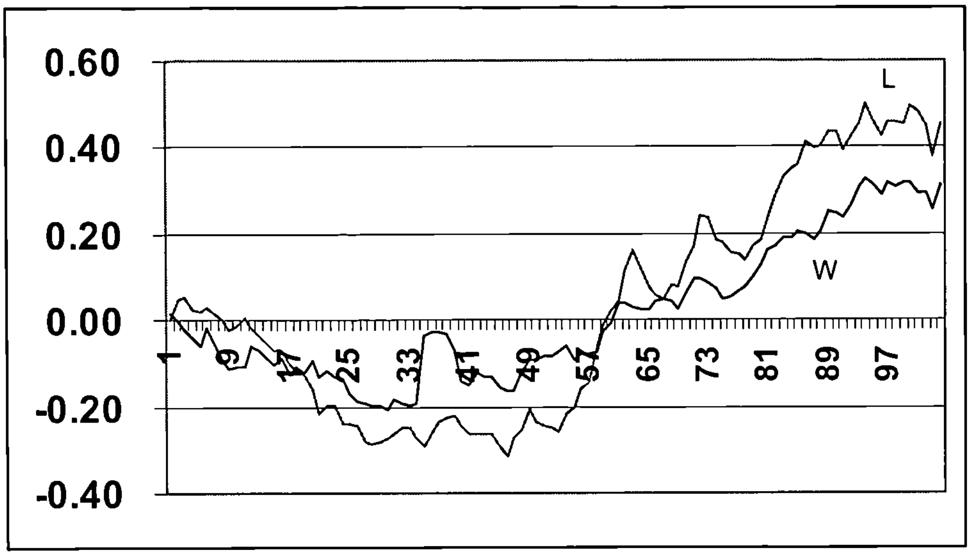


Figure 4.22
ACARs of Winner (W) and Loser (L) Portfolio
(Above Risk Free Rate returns, 3-year formation & testing periods)

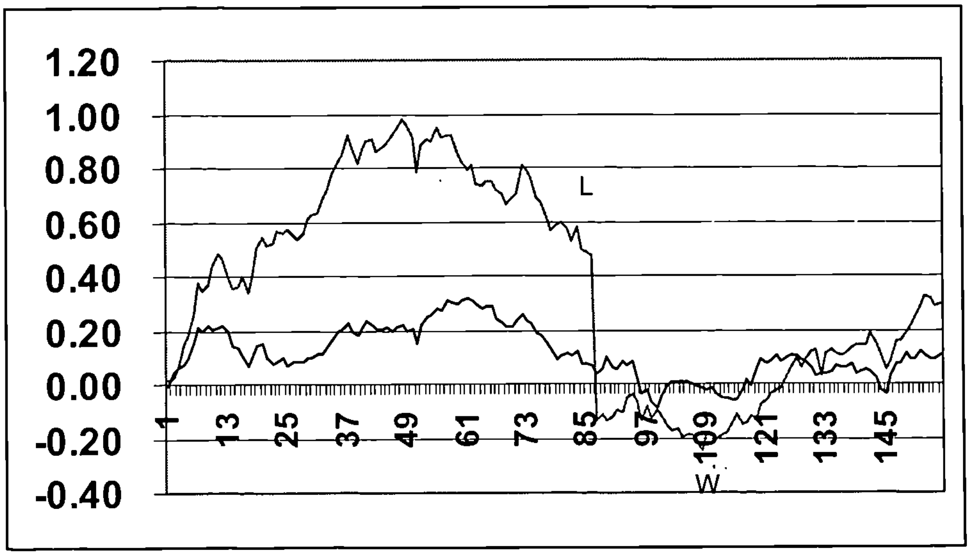


Figure 4.23
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 1-year formation & testing (excluding January))

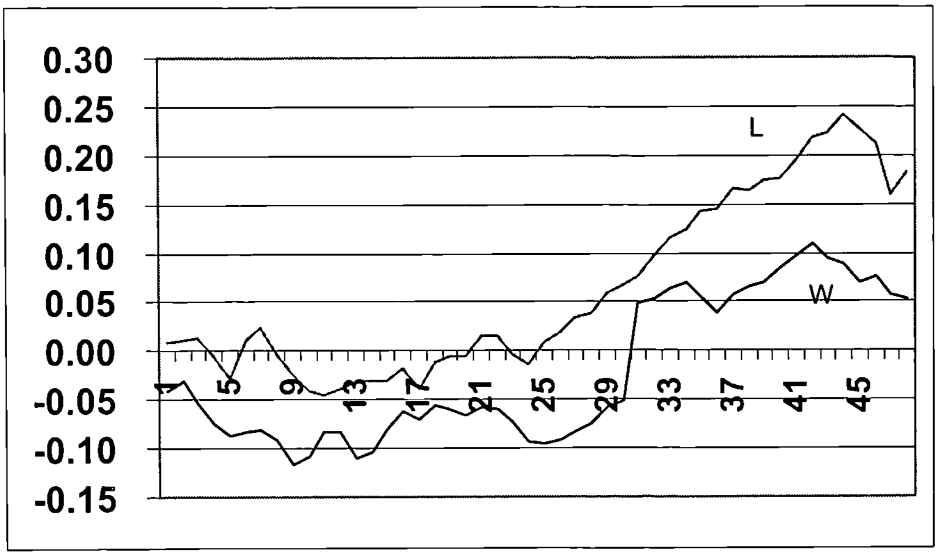


Figure 4.24
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 1-year formation & testing (excluding January))

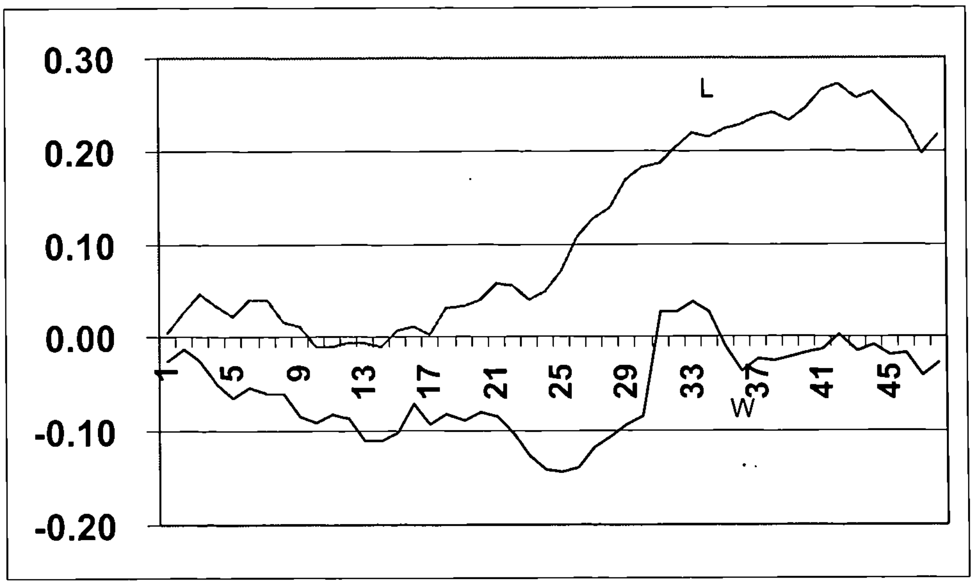


Figure 4.25
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 1-year formation & testing (excluding January))

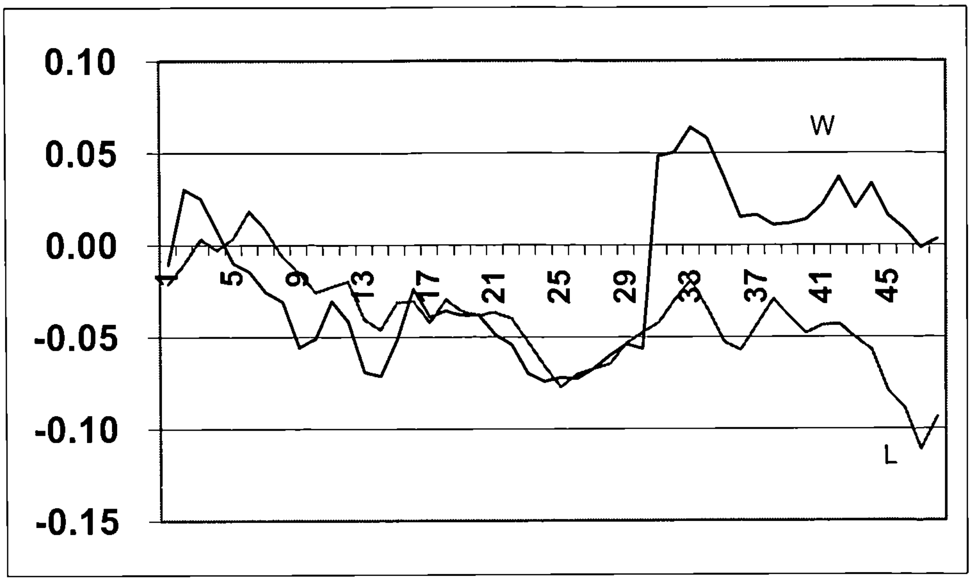


Figure 4.26
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 2-year formation & testing (excluding January))

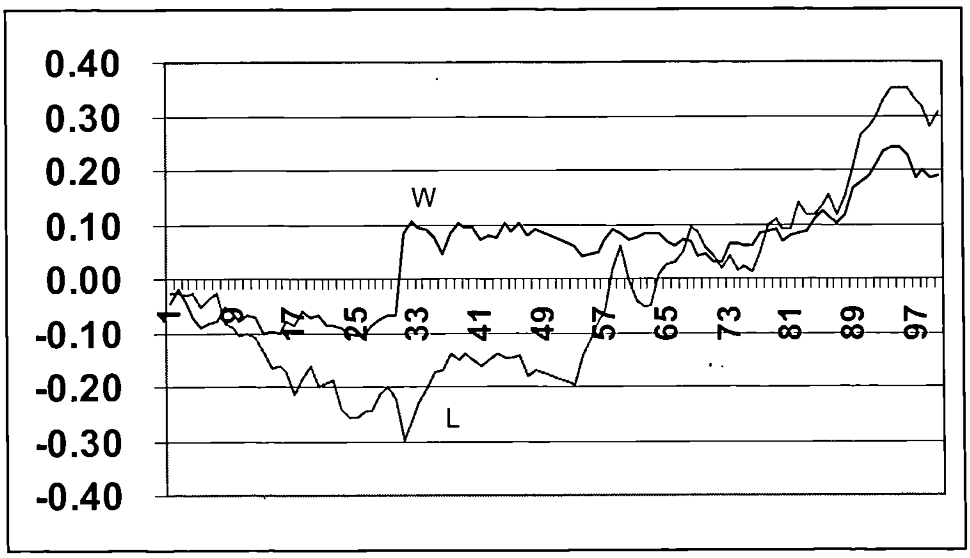


Figure 4.27
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 2-year formation & testing (excluding January))

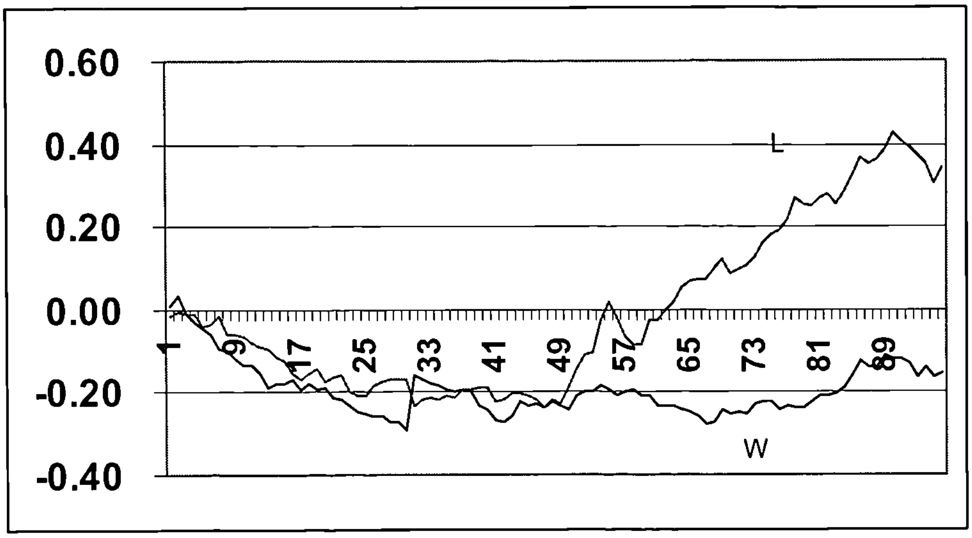


Figure 4.28
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 2-year formation & testing (excluding January))

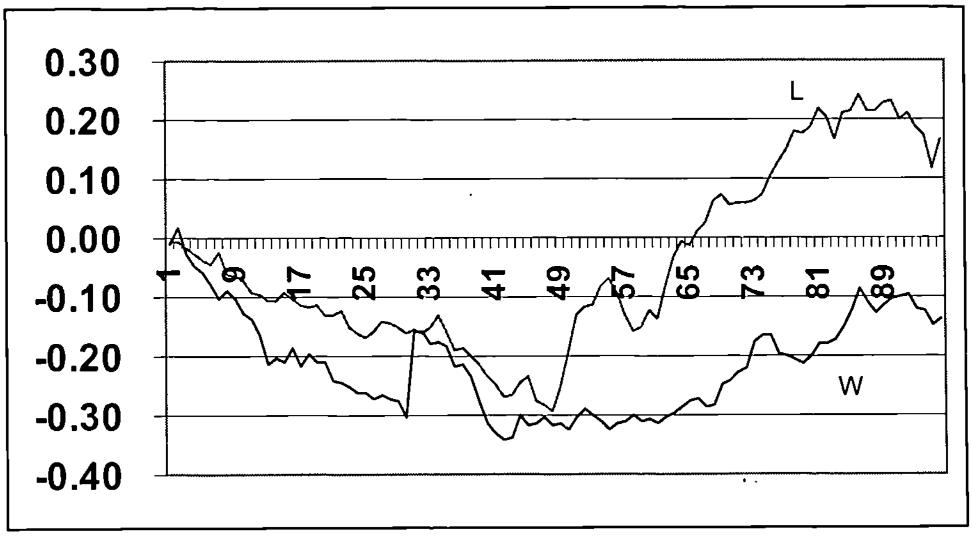


Figure 4.29
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 3-year formation & testing (excluding January))

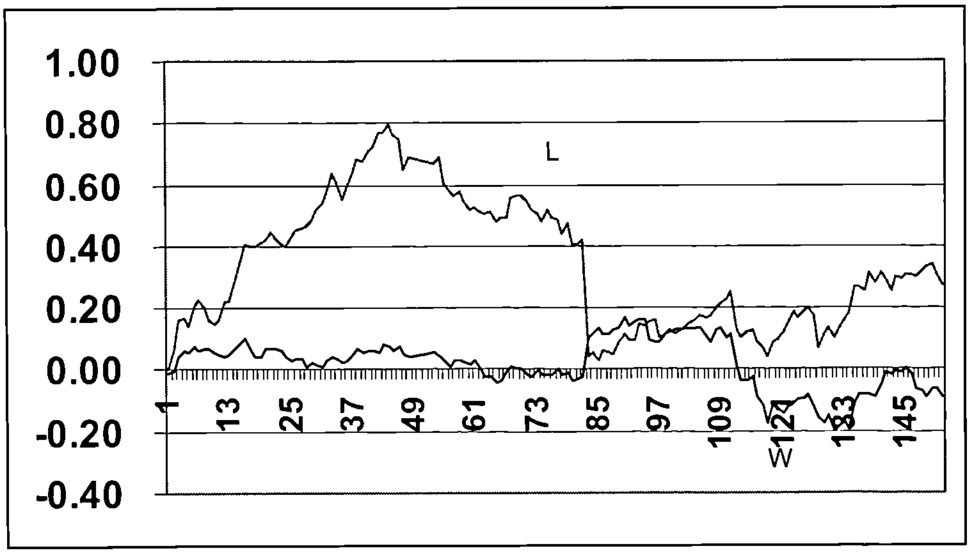


Figure 4.30
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 3-year formation & testing (excluding January))

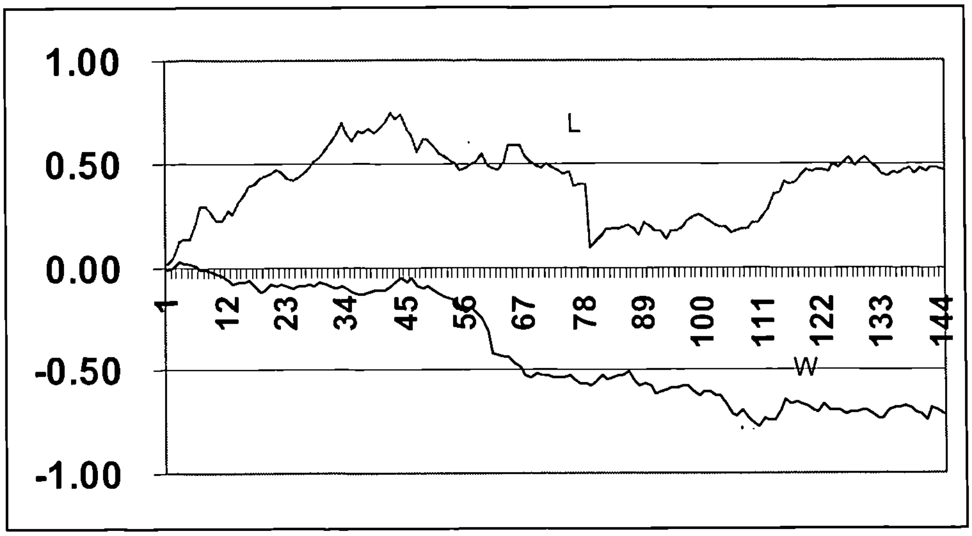


Figure 4.31
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 3-year formation & testing (excluding January))

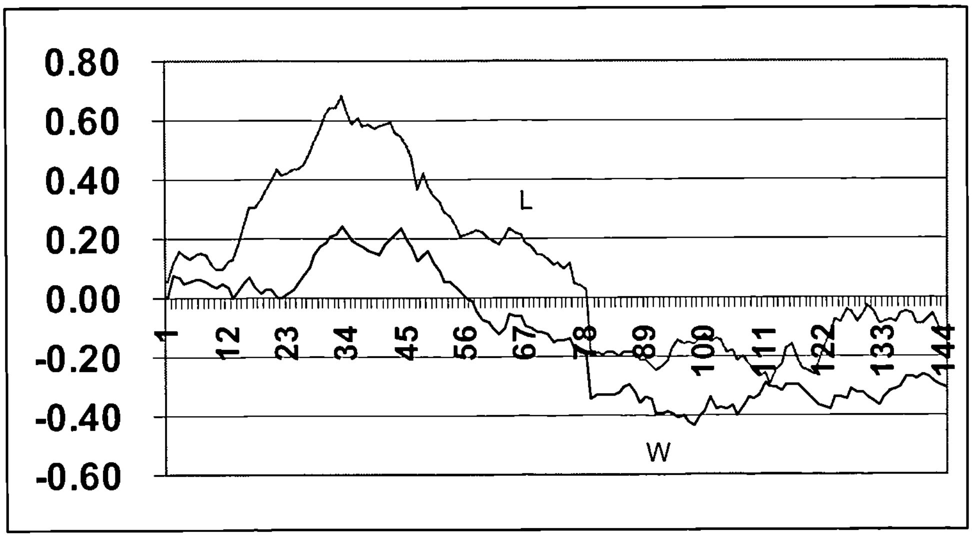


Figure 4.32
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 1-year formation & testing (excluding August))

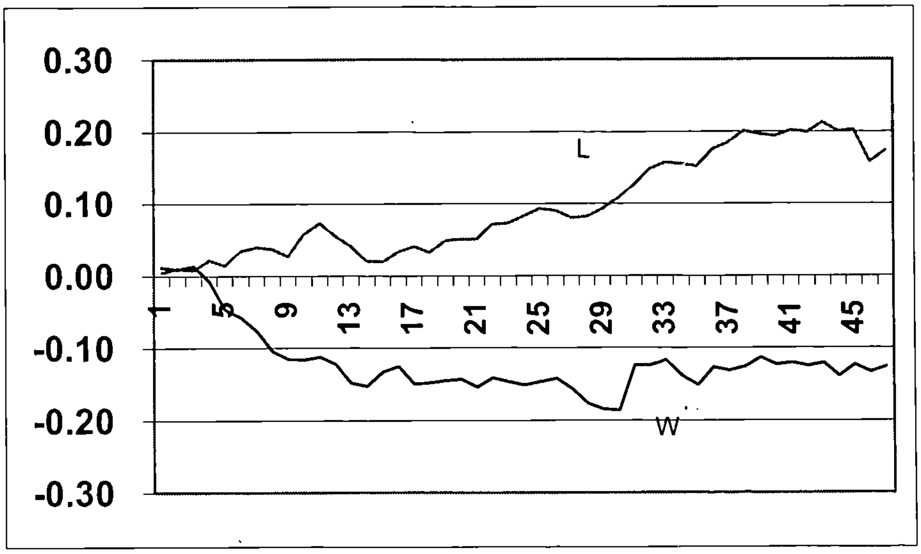


Figure 4.33
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 1-year formation & testing (excluding August))

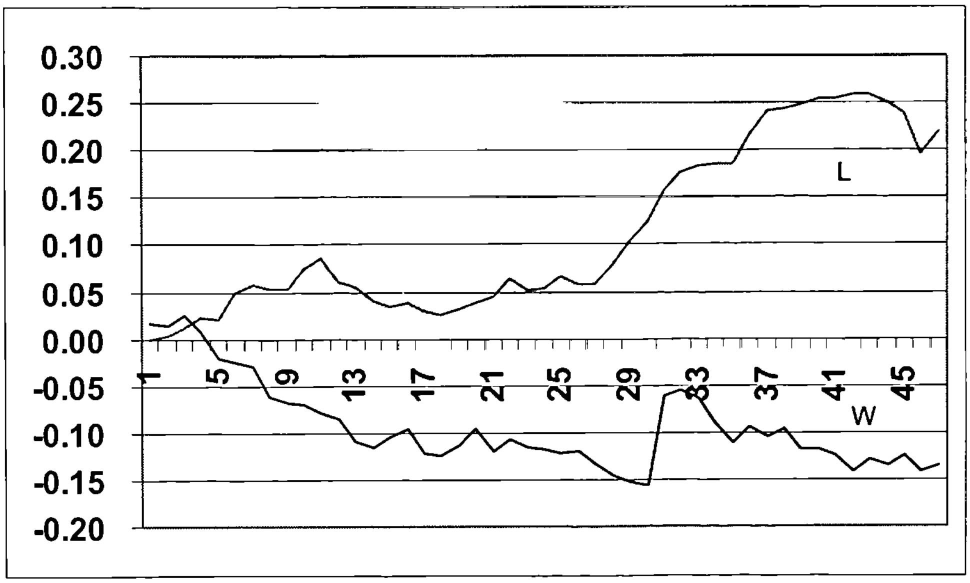


Figure 4.34
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 1-year formation & testing (excluding August))

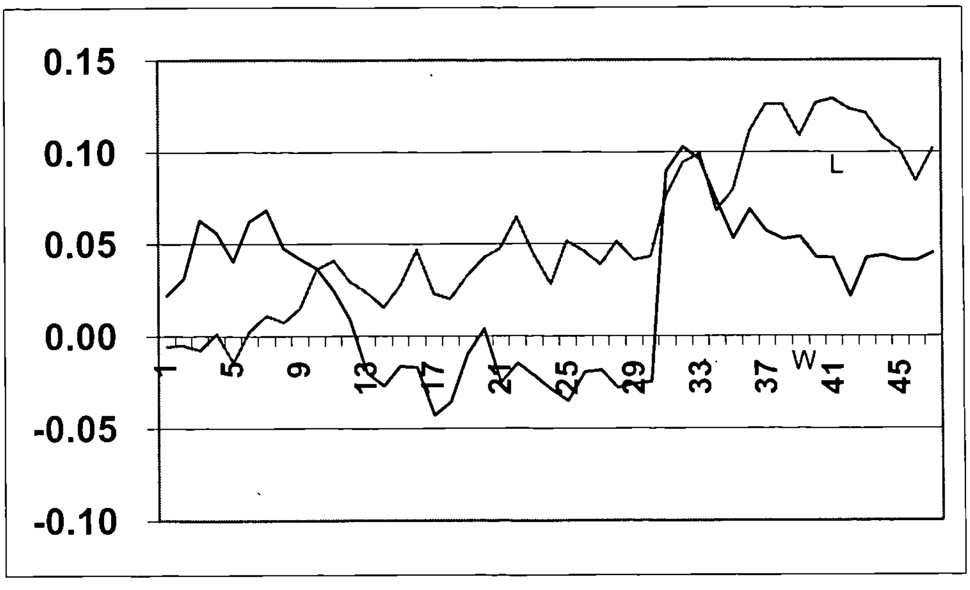


Figure 4.35
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 2-year formation & testing (excluding August))

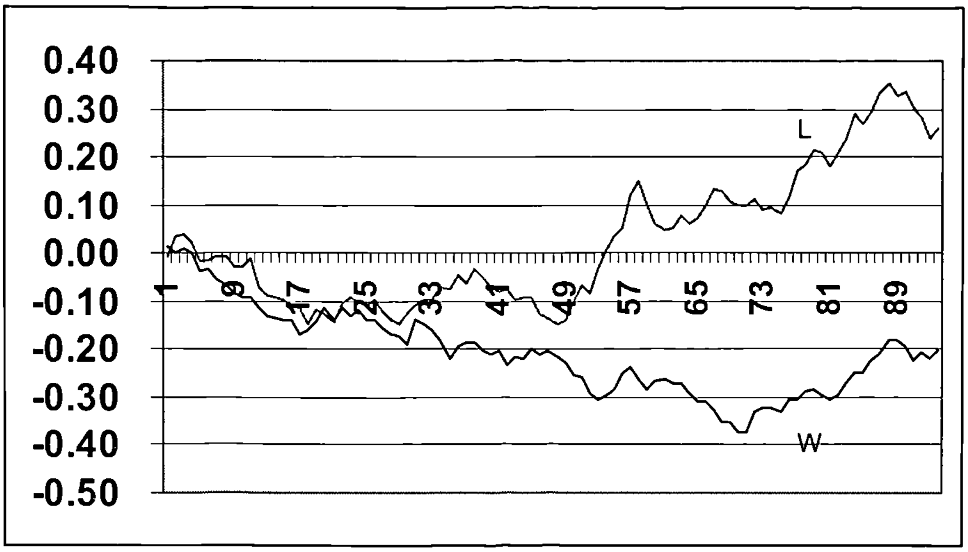


Figure 4.36
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 2-year formation & testing (excluding August))

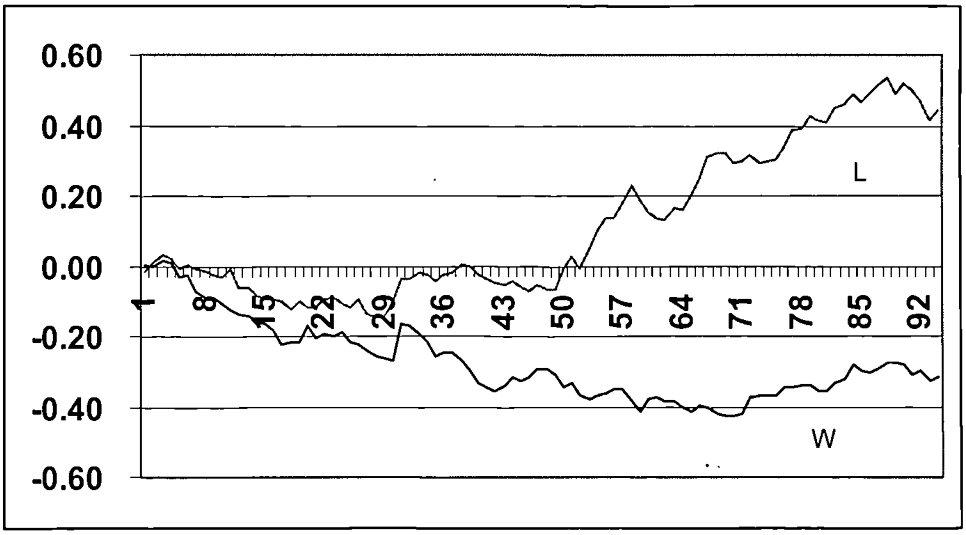


Figure 4.37
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 2-year formation & testing (excluding August))

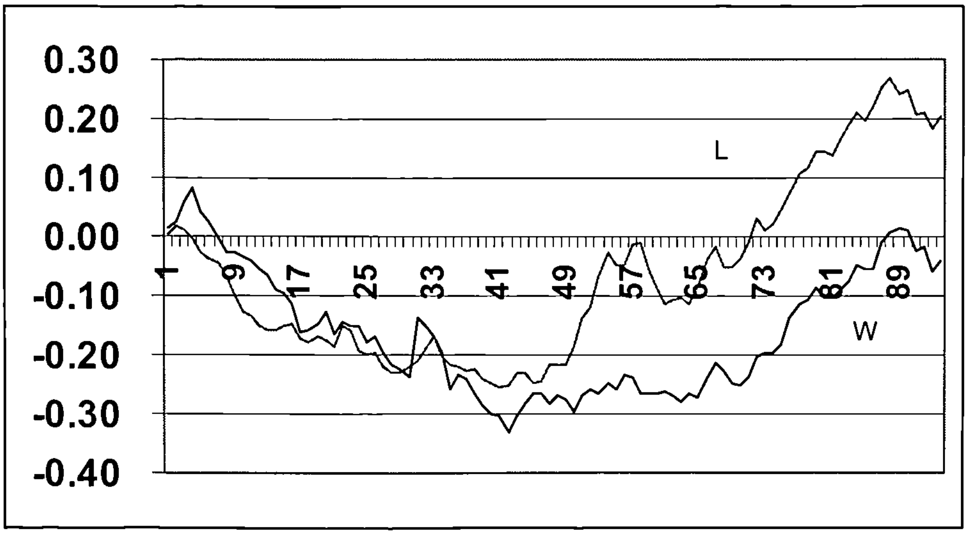


Figure 4.38
ACARs of Winner (W) and Loser (L) Portfolio
(Market-adjusted returns, 3-year formation & testing (excluding August))

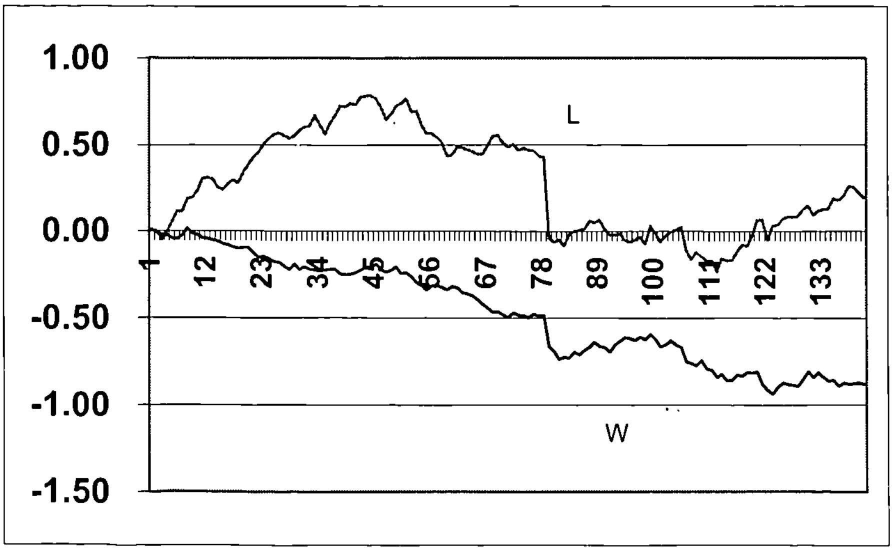


Figure 4.39
ACARs of Winner (W) and Loser (L) Portfolio
(Risk-adjusted returns, 3-year formation & testing (excluding August))

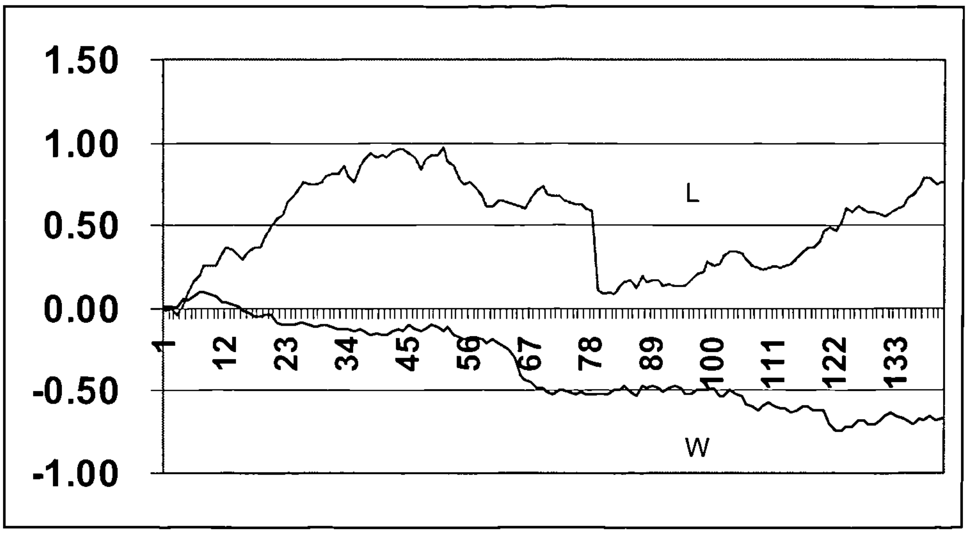
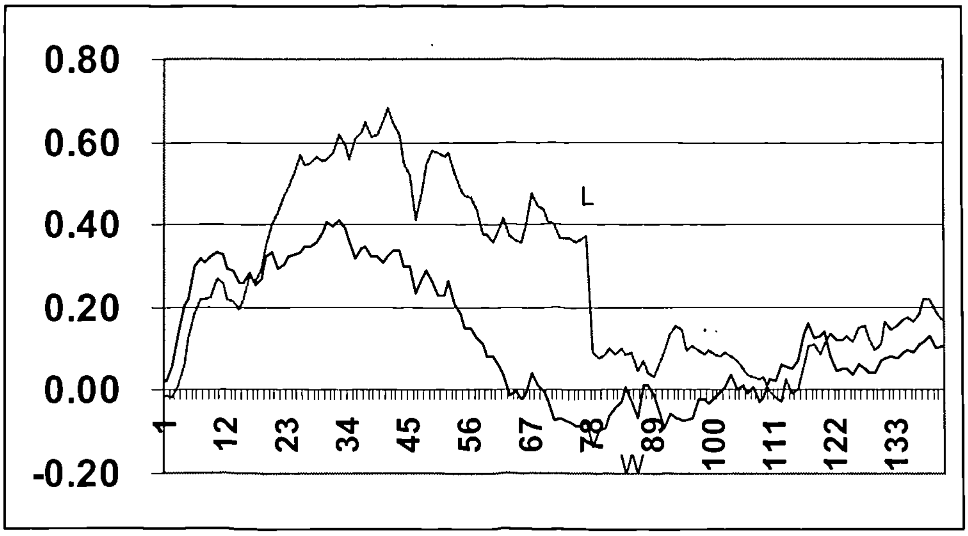


Figure 4.40
ACARs of Winner (W) and Loser (L) Portfolio
(Kalman Filter returns, 3-year formation & testing (excluding August))



CHAPTER V.

PROFITS OF SHORT TERM CONTRARIAN INVESTMENT STRATEGIES DECOMPOSITION UNDER BOTH OVERREACTION & UNDERREACTION

5.1 Introduction

The previous chapter demonstrated that long-term contrarian strategies deliver profits, the magnitude of which falls when time variation in risk is considered. There is however a large portion of profits or loses that remain unexplained. Most of the early literature in the area attributes these profits to the overreaction phenomenon and attempts to benefit from it using a contrarian strategy, as the literature review has exposed (De Bondt & Thaler 1985, 1987, Jegadeesh 1990).

Kaul & Nimalendran (1990) however, suggest that part of the profits might also be related to an underreaction induced lead lag effect. Lo & Mackinley (1990) further suggest on this, that not just some, but most of the profits come from underreaction to common factors. More specifically, some stocks adjust faster to information than others, creating lead-lag effects that can lead to contrarian profits. If there are only two stocks in the market stocks A and B, and stock A leads stock B, then a contrarian will sell stock A once it has in creased in price, to long stock B, which will also increase in price and deliver contrarian profits, but not because of overreaction, but the lead lag effect. Following their suggestion, Abarbanell & Bernard (1992) recommend both overreaction and underreaction as explanations of contrarian profits. Amir & Ganzach (1998), Barberis, Shleifer, and Vishny (1997) and many others also follow this recommendation especially in strictly behavioural finance approaches to contrarian profitability. This a critical issue because identification of the precise source of contrarian profits is imperative for such strategies to succeed.

Jegadeesh & Titman (1995) however show that although underreaction to common news might have some contribution to contrarian profits, this is limited and might be negative in most cases. They conclude that the study of Lo & Mackinley (1990) came to a wrong conclusion due to technical mistakes that exaggerated the contribution of the lead lag effect and diminished the overreaction effect. Lo & Mackinley's study however is very important because it decomposes contrarian profits to portions owed to common factor reactions, firm specific reactions, and factors other than these two, suggesting a model that could differentiate at the same time between overreaction and underreaction. That is why Jegadeesh and Titman build on Lo & Mackinley's study. The outcome however of Jegadeesh & Titman (1995) (JT henceforth) raises more questions than the ones it answers, and their methodology could be improved on several aspects. For instance, they consider size to remain constant through out their study; this is very unrealistic because firm size and risk characteristics change over time (Chan 1988). See for example figures 5.54 to 5.57 in the Appendix (section 5.6.4) for changes in MV's in the sample period for four randomly selected stocks, and figures 5.46 to 5.50 in the same section for changes in the average market betas for five size sorted sub-samples of all the firms in the sample.

The methodology of Lo & Mackinley (1990) and JT is interesting because they both refer to short-term weekly contrarian strategies, while most studies have concentrated on longer-term contrarian strategies that transact once a year at most, and with a usual horizon of around three years or even more; Chen & Sauer (1997) for example use horizons of up to five years. This is the case because it usually takes time for long-term contrarian strategies to work and for losers to become winners. De Bondt & Thaler (1985) find that it takes a year for losers to become winners and vice-versa. Pettengill & Bradford (1990) find a six-month lag before contrarian strategies work, and Chopra & Lakonishok (1992) suggest that it takes a year for such strategies to work. Although very few studies have used weekly trading in the area of contrarian strategies, both JT, and Lo and Mackinley show that short-run contrarian profits are possible.

This chapter is interested in determining whether contrarian profits in the ASE also exist for short-term strategies, by first determining if stock returns are short-run correlated (i.e. predictable). Having done so, it employs short-run contrarian strategies compared to the longer-term strategies in the previous chapter, to address whether very short investment horizons affect results. Underreaction is introduced as a possible explanation for contrarian profitability, in an attempt to explain the portion of profits that remained unexplained by risk changes in the previous chapter. Furthermore, this chapter decomposes profits using the method suggested by JT and Lo & Mackinley (1990), examining over or underreaction to firm-specific information and common factors. This enables the critical evaluation of the economic significance of any of the above, and further supplements the improvement of such strategies, by allowing investors to exploit factors that will deliver a better outcome, and regulators to deal with such factors. However, the chapter does not use a single-factor model like JT, but improves their methodology by means of a multi-factor model, after showing that contrarian profits are related to the two additional factors suggested by Fama & French (1993, 1996) and are not related to the market. Nevertheless, single-factor evidence are also provided in order to measure the extent of the differences related to the two models. Some further insight on the reasons behind the inferiority of the single factor model is offered by: (i) testing whether the single-factor model is improved by using an equally weighted proxy for the market portfolio as opposed to a value-weighted one (Michaely, Thaler & Womack 1995). (ii) Testing whether excluding January (Zarowin 1990) alters results, and (iii) looking into market frictions with respect to the single-factor model. However, as results show, none of the above helps the single factor model outperform the multifactor one. Finally, before attributing possible multifactor model profits to overreaction or underreaction, risk and market frictions are considered for this model as well.

This chapter contributes to the contrarian literature in several different ways. Firstly, it tests for short-term contrarian strategies for the first time in the ASE. Secondly, it decomposes such profits for the first time in the ASE developing market. As already mentioned in the previous chapter's introduction, it is very important to investigate whether phenomena that are at work in the developed US market could also hold for developing markets. One would expect that such phenomena would be more pronounced in less developed markets with larger information asymmetries and a less developed relevant legal framework. Thirdly, it improves on the JT methodology by considering annual rebalancing of size sorted sub-samples, removing the possible bias that JT introduce by creating size sorted sub-samples based on only the first year's Market Values and holding size constant after that. The chances for example that a firm in the smallest (largest) sub-sample in the beginning of the testing period will not grow (reduce in size) in the next fifteen or thirty years are very small. Thus without rebalancing, one might end up analysing the characteristics of a set that no longer holds the qualities it is supposed to, and may come to the wrong conclusions[84]. The chapter also deals with another problem of the JT methodology, that is, JT include in their sample only firms that exist in the beginning of their sample period, and no new firms after that. The chapter's methodology on the other hand, adds stocks in the sample as they become available whenever they meet the criteria set. Furthermore, this section of the thesis investigates whether results based on this methodology are a manifestation of well-known anomalies, or microstructure biases, or the market proxy used. Finally and most importantly, the chapter shows that contrarian short-term profits are unrelated to market risk by regressing contrarian profits on the market factor returns. This indicates that JT might have mistaken when using the market index as their single factor. In place of the single-factor model, a multifactor model similar to the Fama French three-factor model is introduced to the strategy, after finding that the factors are related to contrarian profits. This should allow to account for any portion of returns initially thought to be due to overreaction and/or underreaction, that is really related to risk, by taking into account for factors that act as risk premiums.

The remainder of this chapter is organised as follows: section 5.2 discusses the data and presents evidence of contrarian profits, section 5.3 discuses the profit decomposition methodology, section 5.4 presents results, section 5.5 concludes the chapter, and section 5.6 is the Appendix.

[84] For example, see Appendix section 5.6.4, figures 5.54 to 5.57, for changes in MV's in the sample period for four randomly selected stocks.

5.2 Data, Profits and Testing Methodologies

5.2.1 Data and descriptive statistics

The chapter uses the same data set as in the previous empirical chapter. Stocks are assigned to five size-sorted sub-samples, each of which contains 20% of available firms as follows: every year stocks are ranked on the basis of the previous year-end stock market capitalisation[85]. For example, to create the five sub-samples for the year 1997, all 173 stocks available for this year are sorted according to the last market value of 1996 (the previous year). This gives 36 firms in the smallest sub-sample, 34 firms in the three next sub-samples, and 35 firms in the largest firms sub-sample. The procedure is repeated every year, allowing for five size-sorted sub-samples per year, for eleven years. Tests are then performed on the whole sample as well as on the five sub-samples.

Table 5.1 (panel A) presents descriptive return statistics for the five size-sorted sub-samples and the all-stock sample. As can be seen, the highest mean weekly return is that of the smallest stock sub-sample (0.56%) while the lowest is that of the medium stock sub-sample (0.25%). The highest total risk (standard error) is that of the small stock sub-sample (0.0497) while the lowest is that of the largest stock sub-sample (0.0421). Note that the smallest stock sub-sample has only the second lowest total risk (0.0430). The mean weekly return for the all-stock sample lies in between (0.336%), while the standard error is the smallest

[85] There are 79 out of 173 firms in the first year's sub-samples, and 81, 116, 131, 137, 148, 168, 173, 173, 173, 173 firms for each of the remaining years. Market value data are obtained from Datastream.

(0.0027). The kurtosis coefficients indicate that returns distributions may have thicker tails than normal[86], while the skewness coefficients are all positive indicating skewness to the right. In order to test whether these differences in mean returns across size quintiles are statistically significant, a pair-wise Wald test is employed. The null hypothesis is that the mean return of every size quintile is equal to the mean return of every other size quintile, and Panel C in Table 5.1 presents the probabilities for the resulting Wald statistics. The null hypothesis is accepted in every case; thus, the mean returns across size quintiles do not appear to be statistically different.

[86]See the Appendix (5.6.4) for plots of average returns and their distributions against normal distribution (figures 5.13 to 5.26).

Table 5.1
Descriptive Statistics & Tests for Serial Correlation in Stock Returns

	All Stocks	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
			Panel A: Descriptive Statistics			
Mean	0.00336	0.00562	0.004153	0.00250	0.00266	0.00295
St. Error	0.00273	0.04302	0.049796	0.04947	0.04809	0.04211
Min	-0.00444	-0.24272	-0.28733	-0.31075	-0.25074	-0.15236
Max	0.01589	0.20219	0.26842	0.26285	0.25226	0.18244
Skewness	0.38946	0.31893	0.11012	0.15872	0.23294	0.35052
Kurtosis	2.90071	6.01931	7.69008	7.27277	4.96318	2.68803

Panel B: Serial Correlation

Order	ASE	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
1	0.122[0.004]	0.245[0.000]	0.253[0.000]	0.145[0.001]	0.152[0.000]	0.153[0.000]
2	0.128[0.000]	0.112[0.000]	0.114[0.000]	0.091[0.000]	0.033[0.001]	0.063[0.000]
3	0.035[0.000]	0.031[0.000]	0.029[0.000]	0.042[0.001]	0.047[0.002]	0.063[0.001]
4	0.022[0.001]	0.127[0.000]	0.124[0.000]	0.088[0.000]	0.027[0.000]	0.019[0.001]

Panel C:
Are Differences in Mean Returns across Size Quintiles Statistically Significant?

$\bar{r}_{smallest} = \bar{r}_{small}$: [0.41]	$\bar{r}_{smallest} = \bar{r}_{smedium}$:[0.08]	$\bar{r}_{smallest} = \bar{r}_{large}$: [0.10]	$\bar{r}_{smallest} = \bar{r}_{largest}$: [0.14]
	$\bar{r}_{small} = \bar{r}_{medium}$: [0.42]	$\bar{r}_{small} = \bar{r}_{large}$: [0.47]	$\bar{r}_{small} = \bar{r}_{largest}$: [0.55]
		$\bar{r}_{medium} = \bar{r}_{large}$: [0.95]	$\bar{r}_{medium} = \bar{r}_{largest}$: [0.84]
			$\bar{r}_{large} = \bar{r}_{largest}$: [0.95]

Notes to Table 5.1:

Returns are continuously compounded, defined as the first difference of the logarithmic price levels and all data are collected from Datastream. Stocks are assigned to five size-sorted sub-samples that contain 20% of firms as follows: every year stocks are ranked on the basis of the previous year-end stock market capitalization. The procedure is repeated every year, allowing for five size-sorted sub-samples per year, for a period of eleven years, from smallest to largest. The "All Stocks" category contains all stocks in the sample, while ASE denotes the returns in the Athens Stock Exchange General Price Index (ASE GPI). The numbers in brackets (Panel B) are probabilities for the Ljung-Box (1978) Q* statistic for testing the Null Hypothesis of "No Serial Correlation" in stock returns. The statistic is computed as follows: $Q^* = n(n+2)\sum_{j=1}^{p} r_j^2/(n-j)$ approximately distributed as χ_p^2, with p degrees of freedom.

Panel C presents probabilities for a Wald test for the null hypothesis that the mean return of every size quintile is equal to the mean return of every subsequent size quintile.

5.2.2 Serial correlation in returns

If serial correlation is present in the data, it can lead to short-run contrarian profits. More specifically, if there is positive serial correlation in the five size-sorted portfolios for ASE, while there is negative serial correlation in individual stock returns, then contrarian profits would be due to two main reasons. One reason is the negative serial correlation in individual stock returns that is consistent with the return reversals suggested by De Bondt and Thaler's (1985) overreaction hypothesis. The other reason being that for portfolios created by these negatively autocorrelated assets to have a positive correlation, then the cross serial correlation of the assets must be positive. This stems from the fact that the first order autocovariance of a portfolio can be given as the sum of the first order individual (own) autocovariances and the cross autocovariances between the assets in the portfolio. So, if the individual asset autocovariances are negative on average while portfolio autocovariances are positive, then for this to happen, the cross-autocovariances must not only be positive, but at the same time they must also be larger than the individual assets' negative autocovariances to exceed their collective negative effect (see Lo and Mackinley 1990).

As mentioned, negative serial correlation in individual stock returns, can lead to short-run contrarian profits. For example, a contrarian strategy that each period shorts past winners and goes long past losers can benefit from first order negative serial correlation in individual stock returns, because this will transform winners to losers and losers to winners, and a contrarian strategy will then deliver profits. Table 5.2 reports the results for testing for first order serial correlation in the returns of all stocks in the sample that trade frequently (see footnote 87) along with their respective probabilities. The probabilities are the Ljung-Box (1978) Q* statistic for testing the Null Hypothesis of "No Serial Correlation" in stock returns. The results indicate that 72.6% of firms have negative first order serial correlation, 50% of which are significant at the 10% level, suggesting that contrarian profits due to return reversals may be possible.

It is well known that negative serial correlation can be due to the bid-ask bias (Lo and Mackinley 1990). This however is not the case here, since the ASE operates an order-driven system and not a market-maker system where bid and ask prices are provided by the market makers. Furthermore, trading is computerised and orders are matched by price, number of shares offered, and the time they are introduced, and orders are initiated from security firms via computer terminals in their offices or in the exchange floor. In the absence of market makers and due to the trading system, there is no bid-ask spread in the ASE (see also Milonas and Travlos 2001).

Table 5.2
1st order Serial Correlations

Firm	C	P	Firm	C	P	Firm	C	P
x1	-0.151*	0.001	**x50**	0.063	0.136	**x99**	0.136	0.001
x2	0.028	0.593	**x51**	-0.048	0.283	**x100**	0.049	0.250
x3	-0.073	0.250	**x52**	-0.007	0.884	**x101**	-0.047	0.287
x4	-0.003	0.955	**x53**	-0.017	0.758	**x102**	0.023	0.589
x5	-0.022	0.680	**x54**	-0.042	0.322	**x103**	0.057	0.177
x6	-0.048	0.258	**x55**	-0.276*	0.000	**x104**	0.044	0.296
x7	0.082	0.057	**x56**	-0.055	0.196	**x105**	0.042	0.320
x8	-0.082	0.170	**x57**	0.039	0.352	**x106**	-0.099**	0.019
x9	-0.034	0.419	**x58**	0.048	0.262	**x107**	-0.098**	0.017
x10	-0.153*	0.000	**x59**	-0.040	0.470	**x108**	-0.115*	0.007
x11	-0.008	0.853	**x60**	-0.128*	0.003	**x109**	-0.186*	0.000
x12	0.136	0.002	**x61**	-0.078**	0.067	**x110**	-0.077**	0.085
x13	-0.024	0.682	**x62**	-0.058**	0.068	**x111**	-0.022	0.602
x14	-0.021	0.730	**x63**	0.036	0.457	**x112**	-0.075**	0.078
x15	-0.366*	0.000	**x64**	-0.069	0.198	**x113**	0.062	0.153
x16	0.011	0.790	**x65**	0.124	0.004	**x114**	-0.015	0.770
x17	-0.103*	0.025	**x66**	-0.357*	0.000	**x115**	-0.063	0.160
x18	-0.042	0.475	**x67**	0.004	0.937	**x116**	-0.003	0.954
x19	-0.072**	0.089	**x68**	0.000	0.992	**x117**	-0.007	0.875
x20	-0.018	0.747	**x69**	0.104	0.061	**x118**	-0.133*	0.002
x21	0.204	0.000	**x70**	-0.264*	0.000	**x119**	-0.087*	0.039
x22	0.053	0.343	**x71**	-0.138*	0.001	**x120**	-0.026	0.538
x23	-0.133*	0.005	**x72**	-0.060	0.273	**x121**	0.064	0.159
x24	-0.254*	0.000	**x73**	-0.006	0.911	**x122**	0.032	0.486
x25	-0.187*	0.000	**x74**	-0.169*	0.000	**x123**	-0.211*	0.000
x26	-0.037	0.385	**x75**	-0.002	0.977	**x124**	-0.218*	0.000
x27	-0.052	0.224	**x76**	-0.077*	0.089	**x125**	-0.101*	0.017
x28	-0.060	0.162	**x77**	0.166	0.003	**x126**	-0.025	0.577
x29	-0.025	0.559	**x78**	-0.103*	0.024	**x127**	0.085	0.044
x30	0.010	0.812	**x79**	-0.094**	0.092	**x128**	-0.013	0.758
x31	0.026	0.532	**x80**	0.084	0.141	**x129**	-0.084**	0.059
x32	-0.173*	0.000	**x81**	-0.097*	0.023	**x130**	-0.172*	0.000
x33	-0.156*	0.000	**x82**	0.018	0.725	**x131**	-0.139*	0.001
x34	-0.030	0.477	**x83**	-0.086	0.116	**x132**	-0.042	0.355
x35	-0.030	0.547	**x84**	-0.114*	0.007	**x133**	-0.092*	0.036
x36	-0.153*	0.006	**x85**	-0.069**	0.084	**x134**	-0.142*	0.001
x37	-0.083	0.140	**x86**	0.031	0.470	**x135**	0.059	0.200
x38	-0.027	0.532	**x87**	-0.070**	0.096	**x136**	0.174	0.001
x39	-0.006	0.915	**x88**	-0.065	0.133	**x137**	-0.018	0.672
x40	-0.118*	0.007	**x89**	-0.119*	0.011	**x138**	-0.028	0.530
x41	-0.111*	0.012	**x90**	0.044	0.535	**x139**	-0.089*	0.036
x42	-0.004	0.948	**x91**	-0.064	0.366	**X140**	0.018	0.679
x43	0.037	0.452	**x92**	0.033	0.440	**x141**	-0.033	0.438
x44	-0.009	0.866	**x93**	0.048	0.258	**x142**	0.052	0.219
x45	0.010	0.863	**x94**	-0.161*	0.000	**x143**	-0.106*	0.012
x46	-0.070**	0.090	**x95**	-0.093*	0.028	**x144**	0.032	0.454
x47	-0.059	0.195	**x96**	-0.060	0.168	**x145**	-0.012	0.776
x48	-0.081**	0.075	**x97**	-0.001	0.989	**x146**	-0.083*	0.049
x49	-0.059	0.161	**x98**	-0.239*	0.000			

Notes to Table 5.1:
C: correlation coefficient; P: probability. Probabilities are the Ljung-Box (1978) Q* statistic for testing the Null Hypothesis of "No Serial Correlation" in stock returns. The statistic is computed as: $Q^* = n(n+2)\sum_{j=1}^{p} r_j^2/(n-j)$ approximately distributed as χ_p^2, with p degrees of freedom.

As discussed in the beginning of this subsection, given the negative autocorrelations of assets, if the portfolio autocorrelation is positive, then this will indicate positive cross autocorrelations. Table 5.1 (Panel B) reports the results for testing for serial correlation in the returns of all the size groups (or portfolios in other words), for 1, 2, 3, and 4 lags. Numbers in brackets are probabilities for the Ljung-Box (1978) Q* statistic for testing the Null Hypothesis of "No Serial Correlation" in stock returns and indicate that for all size-groups and all lags reported, the null hypothesis is rejected, and there is positive serial correlation in the overall portfolios. Furthermore, as can be seen in Table 5.2A, not only the contemporaneous cross-serial correlations between the size-sorted portfolios are all large and positive (Panel A), but also the relationship between contemporaneous and lagged returns is also positive (Panels B & C). This is an indication of a lead lag effect between stocks, and it is more prominent for the correlation of contemporaneous larger stock returns with lagged smaller stock returns (Panel C), than it is for the contemporaneous values for the smaller stocks and the lagged values for the larger stocks (Panel B). In other words, it seems that if there is a lead-lag relationship, then, it is more likely that the larger stocks lead the smaller ones and not the opposite.

Based on the above evidence, it can be suggested that both overreaction and an underreaction induced lead-lag effect (consistent with JT, and Lo and Mackinley 1990) can contribute towards contrarian profits, and that there are both theoretical and practical reasons for looking into the decomposition of each of them, for the ASE.

Table 5.2A
Tests for Cross-Serial Correlation in Stock Returns

Panel A: Contemporaneous Cross-Serial Correlation

	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
Smallest Stocks	-	0.868445	0.813420	0.738897	0.594289
Small Stocks	-	-	0.886447	0.834182	0.659106
Medium Stocks	-	-	-	0.880767	0.684005
Large Stocks	-	-	-	-	0.736106

Panel B: Contemporaneous Smaller Stock and Lagged Larger Stock Cross-Serial Correlation

	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
Smallest Stocks	-	0.191765	0.137289	0.110760	0.046307
Small Stocks	-	-	0.183225	0.141306	0.103463
Medium Stocks	-	-	-	0.139399	0.103091
Large Stocks	-	-	-	-	0.158240

Panel C: Contemporaneous Larger Stock and Lagged Smaller Stock Cross-Serial Correlation

	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
Smallest Stocks	-	0.272061	0.259014	0.299488	0.279572
Small Stocks	-	-	0.233402	0.276685	0.274130
Medium Stocks	-	-	-	0.204908	0.298605
Large Stocks	-	-	-	-	0.283936

Notes to Table 5.2A:

See Notes to Table 5.1. An example that will help understand the relationships in the table is that in: Panel A, Row 1, last cell, tells us that the contemporaneous correlation of largest and smallest stocks is equal to 0.594. Panel B, Row 1, last cell, tells us that the correlation of smallest stocks at time t and largest stocks at time t-1 is 0.046. Panel C, Row 1, last cell, tells us that the correlation of largest stocks at time t and smallest stocks at time t-1 is 0.2796.

5.2.3 Contrarian profits

As discussed above, the evidence of serial correlation in the data suggests that contrarian profits may be possible. In order to examine whether such contrarian profits are present, following JT and Lo and Mackinley (1990), the chapter employs a portfolio strategy that involves shorting every week the previous week's winners, and going long on previous week's losers. The zero-investment portfolios are therefore re-balanced every week, and the profits for the portfolio, π_t, are estimated as:

$$\pi_t = -\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - \bar{r}_{t-1})r_{i,t} \tag{5.1}$$

where:

$r_{i,t}$ is the return on stock i at time t,

$\bar{r}_{t-1}$ is the return on an equally weighted index from all stocks at $t-1$, and

N is the number of stocks in the portfolio

Table 5.3, reports the average weekly π_t for all size groups, and under different assumptions, in order to examine the effects of different market frictions such as thin trading. For example, Panel A, reports the profits for all size groups when all stocks are included in the sample (173 stocks). The profits (π x 10^3) are -0.0328 for the smallest stocks group, 0.2611 for the small stocks group, 0.2892 for the medium stocks group, 0.4461, for the large stocks group, 0.9061 for the largest stocks group, and 0.2577 for the all stocks group. Furthermore, these profits appear statistically significant for all sub-samples except the smallest one. Note that, for the same strategy in the US, JT report average weekly contrarian profits (π x 10^3) of 0.6150, 0.3246, 0.2261, 0.1475, 0.0839, and 0.2619 for similar size groups, respectively (see also Lo and MacKinlay 1990). In other words, while in the US contrarian profits decline as one moves from small stocks to large stocks the opposite seems to happen in the ASE. Indeed the largest profits are observed for the largest stock group, the profits for the medium-size stock group however are similar for both markets, but this point shall be revisited later.

5.2.3.1 Contrarian profits, risk and market frictions

As just witnessed, contrarian profits seem to exist in the ASE. However, many markets, especially emerging ones, often exhibit features such as infrequent and/or thin trading (Dimson 1979, Lo and MacKinlay 1990, Miller et al. 1994, Antoniou et al. 1997). Thus, in order to investigate whether the auto-correlation in stock returns is indeed caused by market frictions, the chapter first excludes from the sample the stocks that trade infrequently[87] and re-estimates contrarian profits, living 146 stocks in all-sample category. The contrarian profits with this restricted sample are also reported in Table 5.3 (Panel B). The contrarian profits remain statistically significant, however, the economic significance is slightly

[87] That is, if any of the 173 stocks does not trade for more than 4 consecutive weeks it is removed from the sample for that year. This gives us for 1990 to 2000 50, 55, 90, 115, 125, 130, 140, 150, 150, 160 and 158 firms, in each year respectively. Distributing these in each size sub-sample between 1990 and 1999, we have 10, 11, 18, 23, 25, 26, 28, 30, 30 and 32 firms (for 2000 we have 34 firms in the smallest group and 31 in each of the remaining groups). For the all-sample group, we remove stocks that have zero returns for a period longer than two months and remove stocks that trade once between months, and as a result, we have 146 firms.

altered: for example, for the largest sub-sample the profits are now 0.5592 (from 0.9061 in Panel A) while for the smallest sub-sample they are 0.3268 (from -0.0328 in Panel A). Smaller firms, more prone to such strategies now deliver contrarian profits, and largest firms exhibit much lower profits, consistent with Zarowin (1990) these figures show that portion of the full sample profits in Panel A is possibly due to infrequent trading. Therefore, this sample of frequently trading firms will also be used to perform further tests for the presence of contrarian profits.

Removing firms that do not trade for four consecutive weeks has improved the sample, however it is obvious that there might still be firms that trade every other week in the sample. In order to further investigate the effect of thin trading on contrarian profits, two different procedures are utilised to obtain the *thin trading adjusted returns* as follows (see for further details Miller et al. 1994, and Antoniou et al. 1997):

(i) Ordinary Least Squares (OLS) is used to estimate a first order Autoregressive [AR(1)] model such as:

$$r_{i,t} = a + br_{i,t-1} + e_{i,t} \tag{5.2}$$

where:

$r_{i,t}$ is the return on stock i at time t,

$r_{i,t-1}$ is the return on stock i at time $t-1$, and

$e_{i,t}$ is the estimated residual of stock i at time t , Then the residuals $e_{i,t}$'s are used for constructing thin trading adjusted returns:

$$r_i^{adj} = \frac{e_{i,t}}{(1-b)} \qquad (5.3)$$

where:

r_i^{adj} is the thing trading adjusted return of stock i at time t,

$e_{i,t}$ is the estimated residual of stock i at time t from (5.2),and

b is the estimated slope coefficient from (5.2)

These thin trading adjusted returns r_i^{adj} are used to compute contrarian profits.

(ii) The same model as in (5.2) is estimated using recursive OLS, given that in emerging markets one might expect a non-constant pattern of thin trading (Antoniou et al. 1997). Equation (5.3) now becomes $r_i^{adj} = \frac{e_{i,t}}{(1-b_t)}$, notice the time subscript for the estimated slope coefficient, which indicates that it is different for each time period t, and not constant as before.

Results are presented in Table 5.3, Panels E (for OLS) and F (for recursive OLS) and show that contrarian profits are still statistically significant and not due to thin trading. Note however that when comparing the AR(1) adjusted results (Panel E), with both the full sample (Panel A) and the frequently trading sample results (Panel B), the profits are smaller in magnitude, which means that some portion of them can be attributed to market frictions. Furthermore, profits for the AR(1) adjusted returns are now in line with the U.S. results of Lo and Mackinley(1990) and JT, since profits are now highest for the smallest firms and drop steadily when moving from smallest to largest firms.

As revealed above, thin trading, does not provide a complete explanation for ASE contrarian profits. Results however might be due to risk miss measurement (Chan 1988, Ball & Kothari 1989), and profits might not be present after considering risk. To account for risk, two methods are used to construct abnormal returns, since Chopra et al. (1992) show that how stock returns are defined is important for the examination of contrarian profits. A single-factor model is first considered as this is usually done in most studies (and JT) and it is useful to have comparable results. This is then extended to a multifactor context by considering that more factors capture risk. More specifically, in order to examine whether contrarian strategies are profitable after exposure to a market factor, the chapter employs the frequently trading sample to compute returns adjusted for market-risk, that is, the residuals $e_{i,t}$ are used as abnormal returns in computing contrarian profits. These residuals come from the market model:

$$r_{i,t} = a_0 + b_0 r_{m,t} + e_{i,t} \tag{5.4}$$

where:

α_0 is a constant, or Jensen's alpha

b_0 is the CAPM Beta: $b_0 = \frac{Cov(r_i, r_m)}{Var(r_m)}$, and

e_{it} is the estimated residual term

Results reported in Table 5.3 Panel C indicate that all profits are statistically significant and slightly higher in magnitude than in Panel B where risk-unadjusted profits are presented. Consequently, profits exist even after considering risk. The slight increase in profits can be related to the increase (more than 10%) on the number of stocks that are negatively correlated when adjusting for risk, which can lead to higher profits as explained.

5.2.3.2 Contrarian profits and multifactor asset pricing models

Although it has been shown that contrarian profits are still possible even when taking into account for risk using a one-factor model, another possible aspect must be considered. Recent evidence seem to suggest that the expected return on a portfolio in excess of the risk-free rate is explained by the sensitivity of its return to three factors (Fama and French, 1993, 1996, FF henceforth). These factors are: (a) the excess returns on a broad market portfolio; (b) the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (SMB, Small Minus Big); and (c) the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (HML, High Minus Low). More specifically, the expected excess return on portfolio *i* is:

$$E(r_i) - r_f = b_i[E(r_M) - r_f] + s_i E(SMB) + h_i E(HML) \qquad (5.5)$$

where r_f is the risk free rate, $E(r_M)-r_f$, $E(SMB)$ and $E(HML)$ are expected premiums and the factor sensitivities are the slopes in the time-series regression:

$$r_i - r_f = a_i + b_i(r_M - r_f) + s_i SMB + h_i HML + e_i$$

In effect, FF have shown that extending the Capital Asset Pricing Model (CAPM) to include additional factors explains the long-term contrarian profits in the US. This, according to FF, occurs because past losers are relatively distressed firms, and past winners are stronger firms. That is why past losers have higher expected returns compared to past winners, and their model is able to capture these two qualities. In order to examine whether short-term contrarian strategies are in fact profitable after they are exposed to these factors, the adjusted returns (i.e. the residuals (e_i) from a regression of returns on three factors similar to the FF ones) are employed to compute contrarian profits:

$$r_{i,t} = a_0 + b_0 r_{m,t} + b_1 SMB_t + b_2 HML_t + e_{i,t} \tag{5.6}$$

The first factor, $r_{m,t}$ is the market portfolio. *SMB* is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks. This factor is constructed as follows: every year stocks are ranked according to the previous year's market capitalization. The top and bottom 20% of stocks are then selected to form two equally-weighted portfolios of high and low capitalization stocks respectively. The factor is constructed as the difference of the returns of the two portfolios. A similar procedure is followed for the construction of the factor *HML*. Every year stocks are ranked according to the previous year's book-to-market ratio. The top and bottom 20% of stocks are then selected to form two equally weighted portfolios of high and low book-to-market stocks respectively. The factor is constructed as the difference of the returns of the two portfolios[88].

Results are presented in Table 5.3 Panel D. They indicate that the contrarian profits are significant for all sub-samples and indeed appear higher than the profits reported in Panels B (frequent traders) and A (full sample's raw returns), with the exception of the profits for the largest stock sub-sample, but they are

[88] See Appendix (section 5.6.4) figures 5.40 to 5.43 for SMB & HML return & distribution plots.

similar to the ones from single-factor risk adjusted returns (Panel C). The increase in the profits is easily explained; as it will be seen in Table 5.5, all contemporaneous coefficients of the HML factor and some of the SMB factor are negative, indicating that controlling for these variables should increase contrarian profits (see for example Chordia & Shivakumar 2002)[89]. For example, the profits for the all-stock sample are 0.4084 (t-statistic: 6.617), for the smallest sub-sample are 0.4650 (t-statistic: 3.896), for the small sub-sample are 0.3977 (t-statistic: 2.513), for the medium sub-sample are 0.4670 (t-statistic: 3.268), and for the large sub-sample are 0.4847 (t-statistic: 4.823). Only for the largest sub-sample the profits are lower than the profits reported in Panel A (0.5427 with a t-statistic of 3.627). The fact that contrarian profits are still significant even after accounting for risk using more than one factors, shows that they are either genuine, or that the factors suggested are not the appropriate and others should be used, but this issue is revisited later.

Overall, results in Table 5.3 suggest that contrarian profits[90] in the ASE are statistically significant and that they are not due to market frictions such as thin and/or infrequent trading, however results are more consistent with other studies for thin-trading adjusted returns as discussed earlier. Furthermore, contrarian strategies are still profitable even after controlling for the exposure to factors such as the market portfolio and the two additional FF factors; however, the profits for the largest sub-sample appear to be reduced while the profits of the

[89] Also, going back to the explanation for increased profits I gave earlier with regards to the difference of the profits for the single-factor risk adjusted returns and raw returns, we find that when using a multifactor model there is an even further increase in the negative serial correlation for individual stocks. This might be another explanation related to the higher profits of the multifactor adjusted returns compared to the raw returns.

[90] See Appendix (section 5.6.4) figures 5.28 to 5.39 for Average Profits and distribution plots

smallest sub-sample appear to be increased after controlling for these factors and/or frictions[91].

Although profits are statistically significant, their economic significance is not known, that is why next, the contrarian profit per Euro long (**Ψ**) [92] are estimated as by Bacmann and Dubois (1998), for all the above-mentioned specifications of returns, as follows:

$$\psi_{t,k} = \frac{\sum_{1=1}^{N_{t-1}} w_{i,t}^{+} r_{i,t}}{\sum_{1=1}^{N_{t-1}} w_{i,t}^{+}} \tag{5.7}$$

where:

$$w_{i,t}^{+} = -\frac{1}{N_{t-1}}(r_{i,t-1} - r_{m,t-1}) \text{ if } r_{i,t-1} < r_{m,t-1} \text{ or 0 otherwise.}$$

The way Ψ is defined; it gives the profits only when the weights are positive, (when each asset lagged returns are lower than the lagged market returns), i.e. it gives the profits for the long position. Dividing with the sum of the weights will deliver Ψ in terms of Euro returns. The results are reported in Table 5.3 (Panels A to F) below the contrarian profits. All Euro profits appear statistically significant at the 5% level and are similar in magnitude for all specifications of returns. For example, the contrarian profit per Euro long for the all-stock sample ranges between 0.0103 (Panel F) to 0.0153 (Panel B). As regards the sub-samples, the contrarian profit per Euro long for the smallest stock sub-

[91] See Appendix (section 5.6.4) figures 5.1 to 5.6 for Average Cumulative Profit Plots

[92] See Appendix section 5.6.4, figures 5.7 to 5.12 for average cumulative profits per Euro long.

sample ranges between 0.0082 (Panel F) to 0.0119 (Panel B), while the contrarian profit per Euro long for the largest stock sub-sample exhibits the highest variation from 0.0041 (Panel F) to 0.0159 (Panel A). Furthermore, Euro profits follow the same increasing and decreasing patterns with the profits (π) reported earlier. Also note, that when looking into the Euro profits of the thin trading adjusted returns (Panel E), they are very similar in most cases to the profits per dollar long reported by JT. For example, the thin trading adjusted Euro profit for the largest sub-sample is 0.0068 while for JT it is \$ 0.006[93]. The figure for the large firms group is 0.0088 while for JT it is \$ 0.0085, the medium firms profit is 0.006 while for JT it is \$ 0.011, for the small firms it is equal to 0.011 while for JT that is \$ 0.015, and for the smallest firms it is 0.011 while for JT it is \$ 0.024. For the full sample, the profit figure is here equal to 0.0114 while for JT it is \$ 0.014. This further supports that thin trading adjustment is needed in developing markets like the ASE.

To summarise thus far, there are statistically (π) and economically (Ψ) significant profits for the ASE. These profits are not due to compensation for risk[94], but they are affected by thin trading, accounting for which reduces their magnitude and drives them to levels consistent with the JT study.

[93] 1 Euro=\$ 1.01, in the time of writing (19/7/2002) and thus figures are comparable.
[94] Provided that the FF factors are the appropriate measures risk.

Table 5.3
Contrarian Profits (π) and their economic significance in Euro (ψ)

	All Stocks	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
Panel A: Full Sample (All Firms – 173)						
$\pi \times 10^3$	0.25766	-0.03277	0.26114	0.28925	0.44609	0.90609
	(3.576)*	(-0.295)	(1.812)**	(2.426)*	(3.674)*	(2.718)*
Ψ	0.01525	0.00826	0.00878	0.0089	0.01179	0.01589
	(5.305)*	(3.41)*	(3.442)*	(2.823)*	(3.251)*	(3.309)*
Panel B: Frequently Trading Firms						
$\pi \times 10^3$	0.36121	0.32682	0.25848	0.41385	0.48490	0.55923
	(5.444)*	(2.274)*	(2.611)*	(2.898)*	(4.163)*	(3.284)*
Ψ	0.01532	0.011860	0.011685	0.011686	0.01260	0.01136
	(5.965)*	(4.135)*	(4.157)*	(2.885)*	(3.578)*	(3.010)*
Panel C: Single-factor Risk Adjusted Returns (Frequently Trading Firms)						
$\pi \times 10^3$	0.36052	0.43603	0.36461	0.45212	0.502395	0.57064
	(5.514)*	(3.608)*	(2.245)*	(3.118)*	(4.271)*	(3.560)*
Ψ	0.01222	0.00870	0.00983	0.00723	0.01067	0.00915
	(5.976)*	(3.654)*	(4.286)*	(2.554)*	(3.539)*	(2.759)*
Panel D: Three-factor Risk Adjusted Returns (Frequently Trading Firms)						
$\pi \times 10^3$	0.40845	0.46499	0.39770	0.46701	0.48466	0.54270
	(6.617)*	(3.896)*	(2.513)*	(3.268)*	(4.823)*	(3.627)*
Ψ	0.01233	0.00931	0.00996	0.00705	0.01083	0.00837
	(6.489)*	(4.033)*	(4.499)*	(2.503)*	(3.846)*	(2.612)*
Panel E: R^{ADJ} For Thin Trading by AR(1) Model (Frequently Trading Firms)						
$\pi \times 10^3$	0.3962	0.64457	0.45417	0.34042	0.40668	0.34167
	(6.888)*	(5.022)*	(3.196)*	(3.238)*	(5.274)*	(3.924)*
Ψ	0.01138	0.0111	0.01114	0.00554	0.00877	0.00685
	(5.018)*	(3.961)*	(4.281)*	(1.923)**	(3.119)*	(2.383)*
Panel F: R^{ADJ} For Thin Trading by Recursive AR(1) (Frequently Trading Firms)						
$\pi \times 10^3$	0.3613	0.3559	0.2901	0.3582	0.5013	0.3601
	(7.085)*	(3.451)*	(2.934)*	(4.571)*	(6.395)*	(5.350)*
Ψ	0.01028	0.00821	0.00986	0.00532	0.00850	0.00409
	(4.625)*	(3.021)*	(3.754)*	(2.022)*	(3.100)*	(1.586)

Notes to Table 5.3:

See equation (5.1) for calculation of contrarian profits. Panel A: contrarian profits based on the full sample of stocks. Panel B: 146 firms remain in the full sample after removing firms that trade infrequently. Panel C: risk adjusted returns for the sample in Panel B, employing the residual from: $r_{i,t}=a_0+b_{0t}r_{m,t}+e_{i,t}$. Panel D: three factor adjusted returns for the sample in Panel B, employing the residual from: $r_{i,t}=a_0+b_0r_{m,t}+b_1SMB_t+b_0HML_t+e_{i,t}$. Panel E: thin trading adjusted returns for the sample in Panel B, employing an AR(1) OLS regression: $r_{i,t}=a+br_{i,t-1}+e_{i,t}$, and using as the thin trading adjusted returns: $r^{adj} = e_{i,t} / (1- b)$. Panel F: thin trading adjusted returns for the sample in Panel B, employing an AR(1) recursive OLS.

Contrarian Euro profits (Ψ) are estimated as $\psi_{t,k} = \frac{\sum_{i=1}^{N_{t-1}} w^{+}_{i,t} r_{i,t}}{\sum_{i=1}^{N_{t-1}} w^{+}_{i,t}}$, where $w^{+}_{i,t} = -\frac{1}{N_{t-1}}(r_{i,t-1} - r_{m,t-1})$ if $r_{i,t-1} < r_{m,t-1}$ or 0 otherwise. t-statistics reported in parentheses: $t=\frac{\bar{\pi}}{e.s.e(\bar{\pi})} \sim t_{n-k}$ $t=\frac{\bar{\psi}}{e.s.e(\bar{\psi})} \sim t_{n-k}$, on repeated sampling (* indicates significance at the 5% level; ** indicates significance at the 10% level).

5.3 Selection of Methodology for Decomposition of Contrarian Profits

As the previous subsection has shown short-term contrarian profits are present in the ASE, but one important question that arises at this stage of the analysis, is on the forces that drive such profits. For example, is it overreaction, underreaction, or other factors behind profits? Are these factors common to all stocks or are they firm specific? Answers to these questions will provide market participants with a thorough understanding of the causes of contrarian profits and the ways in which successful strategies can be constructed. To find such answers, profits must be decomposed to their sources. The chapter does so by building on the JT methodology, decomposing contrarian profits to common factor reaction and firm specific reaction, allowing this reaction to be over- or underreaction. This is very important since systematic overreaction to firm specific news has been shown to contribute to contrarian profits, while systematic overreaction to common factors could either increase or decrease them. The methodology allows to evaluate the extent to which overreaction (or delayed reaction) to firm specific information has the same impact on contrarian profits as overreaction (or delayed reaction) to common factors.

In their decomposition of US contrarian profits JT employed one factor, namely the Market factor, but as discussed above, FF have shown that a three-factor model may better describe long-term stock returns. One way to investigate whether contrarian profits are related to one common market factor or to the FF factors in the short-term though, is to obtain estimates and examine their significance. That is, estimate a regression of profit (π) on the market factor (M):

$$\pi_t = \alpha + \beta r_{m,t} + e_{i,t} \quad (5.8)$$

If α is insignificant, and β is significant, then it can be suggested that the market factor is related to profits, and explains them, and therefore additional factors are not needed. This does not need any special explanation and can be based on the suggestion of basic econometrics that: if the explanatory variable is the only factor capable of explaining the dependent variable, then among other things only the slope coefficient should be significant. If however, α is significant and positive, and β insignificant, then there are profits that are unrelated to systematic risk, in which case the other two factors can be incorporated and profits regressed on them as well:

$$\pi_t = \alpha + \beta_0 r_{m,t} + \beta_1 SMB_t + \beta_2 HML_t + e_{i,t} \quad (5.9)$$

If β_1 and β_2 are significant and positive, with β_0 insignificant, then profits are not related to the market factor, but they relate to the two additional factors. If α is insignificant at the same time, then the model explains contrarian profits completely, however if α is positive and significant, then the three factor model, although superior to the single-factor model, does not explain all contrarian profits but just a portion of them. In this case, the positive and significant α would imply that part of contrarian profits are either genuine or related to other risk factors[95]. In either case, if β_1 and β_2 are significant, we should use the three-factor model to decompose profits and not the one factor model suggested by JT.

[95] This could mean that the most important risk factors accepted in the finance literature are not sufficient and other unknown factors might explain stock returns and contrarian profits. This is another discussion, but it is a possible explanation given that as Davis Fama and French (2000) state, the 3-factor model is itself only an incorrect representation of reality but quite a good one.

Equations (5.8) and (5.9) are estimated for profits defined from (i) raw returns, (ii) market adjusted returns, (iii) 3-factor adjusted returns. They are also re-estimated using White's Heteroskedastisity adjusted standard errors to calculate the t-statistics. Results are presented in Table 5.4, Panels A and B. For example, Panel A presents the results from estimating equation (5.8) for all different specifications of profits. The results indicate that the market factor is unrelated to profits (irrespective of how these are defined). This is, because all the estimated slope coefficients are statistically insignificant, while the constant coefficients are all positive and significant at the 1% level with t-statistics varying from 3.58 to 6.69. However, the additional factors (Panel B) are statistically significant for all profit specifications (at the 1% level most times), and their stronger relationship with the profits is further supported by the correlation coefficients between profits and all three factors, which are stronger for the two additional variables as compared to the market factor. The three-factor model is thus superior because its additional factors are related to profits unlike the single factor model. However, the significant and positive α's, imply that the model captures part and not all of the profits, and perhaps genuine abnormal profits are to be made[96]. Based on the above evidence, the FF model should be used for decomposing profits. Using the single-factor instead would be an attempt to decompose profits based on a factor unrelated to them. If this holds for other datasets, it could have biased results and could be the reason that has lead other studies like JT to believe that the common factor is insignificant for contrarian profits. Most importantly, this can impose structure to the firm specific component as seen in eq. (5.10), making it significant, when it is not.

[96] Assuming that there are not other major factors significantly related to contrarian profits.

Table 5.4
Testing the relationship of contrarian profits with common factors

Profits	Coefficients				
	Panel A				
	α_0	β_M			DW
(a) Using Raw Returns	0.00025	-0.00114			1.8808
	(3.58)*	(-0.70)			
Using Raw Returns (White heteroscedasticity adjusted St. Errors)	0.00025	-0.00114			1.8808
	(3.62)*	(-0.54)			
(b) Using Market Adjusted Returns	0.00035	0.00056			1.8209
	(5.43)*	(0.38)			
Using Market Adjusted Returns (White heteroscedasticity adjusted St. Errors)	0.00035	0.00056			1.8209
	(5.57)*	(0.34)			
(c) Using 3 Factor Adjusted Returns	0.00040	0.001017			1.8070
	(6.50) *	(0.73)			
Using 3 Factor Adjusted Returns (White heteroscedasticity adjusted St. Errors)	0.00040	0.001017			1.8070
	(6.69) *	(0.61)			
	Panel B				
	α_0	β_M	β_{SMB}	β_{HML}	DW
(a) Using Raw Returns	0.00029	-0.00118	-0.00605	-0.01237	1.9033
	(4.23)*	(-0.75)	(-3.32)*	(-5.37)*	
Using Raw Returns (White heteroscedasticity adjusted St. Errors)	0.00029	-0.00118	-0.00605	-0.01237	1.9033
	(4.06)*	(-0.95)	(-2.30)*	(-4.26)*	
(b) Using Market Adjusted Returns	0.00039	0.00055	-0.00435	-0.01373	1.8463
	(6.21)*	(0.39)	(-2.66)*	(-6.64)*	
Using Market Adjusted Returns (White heteroscedasticity adjusted St. Errors)	0.00039	0.00055	-0.00435	-0.01373	1.8463
	(5.59)*	(0.36)	(-2.18)*	(-4.50)*	
(c) Using 3 Factor Adjusted Returns	0.00043	0.00101	-0.00365	-0.01315	1.8303
	(7.30)*	(0.75)	(-2.36)*	(-6.74)*	
Using 3 Factor Adjusted Returns (White heteroscedasticity adjusted St. Errors)	0.00043	0.00101	-0.00365	-0.01315	1.8303
	(7.10)*	(0.66)	(-2.03)*	(-4.70)*	
	Panel C				
	P	M	SMB	HML	
(a) Raw Returns: Correlation of Profits with	1.000	-0.030	-0.134	-0.220	
	P	M	SMB	HML	
(b) Market Adjusted Returns: Correlation of Profits with	1.000	0.016	-0.105	-0.270	
	P	M	SMB	HML	
(c) 3-Factor Adjusted Returns: Correlation of Profits with	1.000	0.031	-0.093	-0.274	

Notes to Table 5.4:
Profits are created in three ways as follows: (a) From RAW RETURNS; (b) From MARKET ADJUSTED RETURNS, (i.e. the residual from the regression $R_{i,t} = a_0 + b_0 R_{m,t} + e_{i,t}$); (c) 3-FACTOR ADJUSTED RETURNS (i.e the residual from the regression: $Ri,t = a_0 + b_0 R_{m,t} + b_1 SMB_t + b_2 HML_t + e_{i,t}$). Profits ($\pi$) are regressed on a market factors as follows: (a) $\pi_t = \alpha + \beta R_{m,t} + e_{i,t}$.; (b) $\pi_t = \alpha + \beta_0 R_{m,t} + \beta_1 SMBt + \beta_2 HMLt\ e_{i,t}$. DW: Durbin Watson statistic. * denotes significance at the 5% level.

A K-factor model that allows equity prices to react both instantaneously and with a lag to factor realizations is used to describe stock returns, based on the suggestions of JT:

$$r_{i,t} = \mu_i + \sum_{k=1}^{K} (b^t_{0,i,k} f_{t,k} + b^t_{1,i,k} f_{t-1,k}) + e_{i,t} \qquad (5.10)$$

where:

μ_i is the unconditional expected return of the i-th stock,

$f_{t,k}$ is the unexpected k-th factor realisation at time t,

$b^t_{0,i,k}$ is the time t sensitivity of stock i to the contemporaneous k-th factor realisation,

$b^t_{1,i,k}$ is the sensitivity of stock i to the lagged k-th factor realisation at time t,

$e_{i,t}$ is the estimated residual representing the firm specific component,

All the usual OLS assumptions are made for the estimators being blue, and based on JT it is assumed that factor sensitivities are uncorrelated to common factor realizations:

$$\mathrm{E}(b^t_{0,i,k} \mid f_{t,k}, f_{t-1,k}, k = 1tok) = b_{0,ik} \text{ , and}$$

$$\mathrm{E}(b^t_{1,i,k} \mid f_{t,k}, f_{t-1,k}, k = 1tok) = b_{1,ik}$$

in addition since $f_{t,k}$ is defined as the unexpected factor realisation, then $\mathrm{cov}(f_{t,k}, f_{t-1,j}) = 0$.

Given the model in (5.10), the cross-serial covariance between i and j returns is given by:

$$\mathrm{cov}(r_{i,t}, r_{j,t-1}) = \sum_{k=1}^{K} \mathrm{E}(b_{1,i,k}^{t} b_{0,j,k}^{t-1})\sigma_{fk}^{2} \tag{5.11}$$

This allows for asymmetry in cross serial covariances. For example, if i reacts contemporaneously to every k factor realisation at time t but j reacts with a partial delay to at least one factor, then the cross serial covariance between j at time t and i at time t-1 will be positive. The cross serial covariance between i at time t and j at time t-1 however will be zero, in which case stock i leads the returns of stock j.

Model (5.10) is similar to a conventional multi-factor model that also allows non-zero lagged factor realizations. If stock i reacts with a delay to common factor k then $b_{1,i,k} > 0$ while if stock i overreacts to the factor then $b_{1,i,k} < 0$. Also, overreaction to firm-specific information induces negative serial correlation in e_i, while underreaction will induce positive serial correlation in e_i. To explain this, if the stock underreacts to the common factor then it will take some time for the common news information component to diffuse, and for the prices to adjust to this news, and so the time t relationship of returns with the lagged value of the common factor *(*time *t-1)* will be positive. If however, there is negative serial correlation due to the initial overreaction to common factor and the later correction, then due to the reversals, the opposite will hold, that is, returns at each period will be negatively related to the common factor of the previous period. Furthermore, assuming that the common factor (or factors in the case of a multifactor model) captures all the common news, what ever is left unexplained by it (and therefore by the model) is considered to be the firm specific component of returns, and it is related to the estimated residual ($e_{i,t}$) of equation (5.10). If there is initial overreaction and then correction to this component as well, then it will be negatively serially correlated with it's past. For underreaction to the firm specific component, the opposite holds.

Under the assumption that equation (5.10) is the return generating process, this chapter following JT decomposes contrarian profits as follows:

$$E(\pi) = -E(\frac{1}{N}\sum_{t=1}^{N}(r_{i,t-1} - \bar{r}_{t-1})r_{i,t}) = -\sigma_{\mu}^{2} - \Omega - \sum_{k=1}^{K}\delta_{k}\sigma_{fk}^{2} \qquad (5.12)$$

where:

$$\sigma_{\mu}^{2} = \frac{1}{N}\sum_{i=1}^{N}(\mu_{i} - \bar{\mu})^{2} \qquad (5.13)$$

$$\Omega \equiv \frac{1}{N}\sum_{i=1}^{N}\operatorname{cov}(e_{i,t}, e_{i,t-1}) \qquad (5.14)$$

$$\delta_{t,k} \equiv \frac{1}{N}\sum_{i=1}^{N}(b_{0,i,k}^{t-1} - \bar{b}_{0}^{t})(b_{1,i,k}^{t} - \bar{b}_{1}^{t}) \qquad (5.15)$$

$$\delta_{k} \equiv E(\delta_{t,k})$$

Where, $\bar{b}_{0,k}^{t}$ and $\bar{b}_{1,k}^{t}$ are the cross-sectional averages of $b_{0,i,k}^{t}$ and $b_{1,i,k}^{t}$, $-\sigma_{\mu}^{2}$ is the cross-sectional variance of expected returns, -Ω is the negative of the average serial covariance of the idiosyncratic component of returns (and is determined by stock price reactions to firm-specific information). If stock prices tend to overreact to firm-specific information and correct the overreaction in the following period, - Ω will be positive (and contribute towards profits in eq. 5.12). The last term in (5.12) is the component of contrarian profits attributable to differences in the timeliness of stock price reactions to common factors. When $\delta_k < 0$ stock price reactions to the k^{th} factor realization contribute positively to contrarian profits and negatively when $\delta_k > 0$.

The above specification might be biased because of changes in factor sensitivities over time according to JT. In particular, the lead-lag structure is likely to be biased downwards and the contribution of firm-specific overreaction is likely to be biased upward because of the change in factor sensitivities. As JT show, if there are two stocks: one that reacts instantaneously all the time, and another that reacts instantaneously half of the time, but with a lag the other half of time, then the unconditional estimates of equation (5.10) for the second stock will be an average of both time periods. This will underestimate the lead lag effect contribution (by $.1875\sigma_f^2$) and overestimate the overreaction contribution (by $.125\sigma_f^2$) based in equation (5.12). To deal with this and allow for possible time-variation in factor sensitivities, the chapter employs the following decomposition of contrarian profits, π. Assuming equation (5.10) describes the return generating process, normally distributed errors and $corr(e_{i,t}, e_{i,t-1}) = \rho, \forall i$, the expected profit at time t conditional on $f_{l,t-1}$ (where l is the squared demeaned laged M, SMB, HML) will be:

$$\mathrm{E}(\pi_t | f_{l,t-1}, e_{i,t-1}) = \sigma_\mu^2 - \sum \delta_l f_{l,t-1}^2 - \rho\theta_{t-1} \tag{5.16}$$

where:

$$\theta_t = \frac{1}{N}\sum_{i=1}^{N} e_{i,t}^2 \tag{5.17}$$

The difference of the decomposition in (5.12) with the later approach in (5.16) is obvious. The first decomposition does not consider time variation in factor sensitivities, since it uses a single number (Ω) the average autocovariance of the error term in relation to the firm specific component, and the variance of each factor σ_{fk}^2 (which is again constant) in relation to the common factor component: $E(\pi) = -\sigma_\mu^2 - \Omega - \sum_{k=1}^{K} \delta_k \sigma_{fk}^2$. However, the second decomposition method (5.16) considers non constant demeaned factors such as $f_{l,t-1}^2$ and θ_{t-1}: $\mathrm{E}(\pi_t | f_{l,t-1}, e_{i,t-1}) = \sigma_\mu^2 - \sum \delta_t f_{l,t-1}^2 - \rho(\frac{1}{N}\sum_{i=1}^{N} e_{i,t}^2)_{t-1}$.

Intuitively, this expression allows to incorporate in tests that if the factor realizations are important for contrarian profits, then larger factor realizations will induce larger contrarian profits. At the same time if firm specific news are responsible for contrarian profits, then increased cross sectional dispersion of the firm specific component shall increase contrarian profits. For example, for the three factors already considered, the contribution of each different component of contrarian profits can be estimated with the following time-series regression:

$$\pi_t = \alpha_0 + \alpha_1 (r_{M,t-1} - \bar{r}_M)^2 + \alpha_2 (SMB_{t-1} - \overline{SMB})^2 + \alpha_3 (HML_{t-1} - \overline{HML})^2 + \gamma\theta_{t-1} + u_t \quad (5.18)$$

In (5.18) $\bar{r}_M$ is the average common market factor return, $\overline{SMB}$ and $\overline{HML}$ are the average returns of the SMB and HML factors respectively. An estimate of the contrarian profits due to delayed reactions to common factors is given by the product of α_i (where i = 1, 2, 3) and the variance of the common factor σ_l^2 (i.e. $\alpha_i\sigma_j^2$, where j = M, SMB, HML) while an estimate of contrarian profits due to overreaction is given by:

$$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}) \tag{5.19}$$

Note that JT use the following model instead of model 5.18 to estimate the contributions:

$$\pi_t = \alpha_0 + \alpha_1 (r_{M,t-1} - \bar{r}_M)^2 + \gamma\theta_{t-1} + u_t$$

where:

$r_{M,t-1}$ is the return on the market portfolio at time *t-1*,

θ_t is created by (5.17) using e_t estimated from (5.10),

$\bar{r}_M$ is the average common factor return,

As has been shown and will further be supported in the next section, this model is not appropriate, because leaving out the two additional factors could bias results and give the false impression of more contrarian profits been related to firm specific information contribution. However, when adding the two factors as results will show, about 50% of the firm specific contribution is actually due to the missing factors.

5.4 Results

Based on the evidence of the previous section regarding the relationship of contrarian profits and the three factors used as proxies for risk, in this sub-section, equation (5.10) is estimated as a multi-factor model, with three factors similar to ones in the FF model (as explained earlier):

$$r_{it} = a_i + b_{0,M} r_{M,t} + b_{1,M} r_{M,t-1} + b_{0,SMB} SMB_t + b_{1,SMB} SMB_{t-1} + b_{0,HML} HML + b_{1,HML} HML_{t-1} + e_{i,t} \tag{5.20}$$

Equation (5.20) is estimated for each stock and the full sample period, and also for each year and each stock in each sub-sample separately, in order to provide estimates of the factor coefficients for each year and each stock, which are subsequently used to obtain the average estimates for each sub-sample.

Tests are initially performed for the sample that is unadjusted for thin trading, that is, the full sample of 173 stocks. Then tests are repeated using the sample of frequently trading firms adjusted for thin trading by the AR(1)[97] model. This will allow the comparison of the results and quantification of the bias had the chapter not corrected for the thin trading problem.

Results from estimating equation (5.20) based on the sample that is not adjusted for thin and/or infrequent trading, are presented in Tables 5.5 & 5.6. More specifically, Table 5.5 provides the average sensitivities of stock returns to the current and lagged factor realizations as well as the estimate of the cross-sectional covariance (δ). The average slope coefficient on the contemporaneous market factor is 0.3947 while the average slope coefficient on the lagged market factor is 0.4851. As regards the reaction to the other two factors, equity returns for all sub-samples also seem to react stronger to lagged factor realizations than to contemporaneous realizations. For example, the average slope coefficient for the lagged SMB factor is 0.2402 while for the contemporaneous SMB factor it is 0.10298 (note the high coefficients for the smallest & small groups), also, the average slope coefficient on the lagged HML factor is 0.1208 while on the contemporaneous HML factor it is -0.0599.

The results seem to suggest that equity returns in the ASE react more strongly to the lagged market factor than to the contemporaneous market factor. This shows that, it either takes time for information to diffuse in the ASE, or that thin trading is present and affects betas Clare et al. (2002). Furthermore, the cross-sectional covariance is negative ($\delta < 0$) for all sub-samples and all factors (except for SMB in the all-stock group), indicating that common factors could contribute positively to profits in the ASE.

[97] Results for Recursive OLS adjusted returns for thin trading are very similar and thus not analysed here. Tables of results are however presented for the reader in the Appendix to the chapter, section 5.6.3, Tables 5.25 to 5.27.

Table 5.5
Average estimates of stock return sensitivities to current and lagged factor realizations

Market Factor	$\bar{b}_{o,M}$	$\bar{b}_{1,M}$	$\hat{\delta}_M$
Smallest Stocks	0.387222	0.367302	-0.29753
	(8.605)*	(8.781)*	
Small Stocks	0.418898	0.472211	-0.35875
	(9.324)*	(9.967)*	
Medium Stocks	0.405345	0.514803	-0.31473
	(9.326)*	(11.293)*	
Large Stocks	0.436037	0.560664	-0.38346
	(10.300)*	(12.152)*	
Largest Stocks	0.325962	0.510672	-0.22153
	(8.733)*	(13.555)*	
Average	**0.394693**	**0.48513**	**-0.3152**
All Stocks	0.879018	0.0931	-0.00209
	(39.546)*	(10.771)*	
SMB	$\bar{b}_{o,SMB}$	$\bar{b}_{1,SMB}$	$\hat{\delta}_{SMB}$
Smallest Stocks	0.356661	0.426043	-0.13247
	(7.982)*	(8.455)*	
Small Stocks	0.160843	0.352298	-0.20662
	(4.202)*	(6.896)*	
Medium Stocks	0.070266	0.290828	-0.14697
	(1.869)**	(6.176)*	
Large Stocks	0.040919	0.181116	-0.11388
	(1.196)	(4.846)*	
Largest Stocks	-0.1138	-0.04926	-0.06076
	(-4.093)*	(-1.497)	
Average	**0.102979**	**0.240205**	**-0.13214**
All Stocks	0.150541	0.387763	0.025649
	(11.854)*	(17.084)*	
HML	$\bar{b}_{o,HML}$	$\bar{b}_{1,HML}$	$\hat{\delta}_{HML}$
Smallest Stocks	-0.06523	0.206242	-0.14814
	(-1.459)	(4.597)*	
Small Stocks	-0.03336	0.160496	-0.10612
	(-0.789)	(3.720)*	
Medium Stocks	-0.08438	0.145911	-0.09911
	(-1.925)**	(3 491)*	
Large Stocks	-0.08189	0.035737	-0.04686
	(-1.875)**	(0.898)	
Largest Stocks	-0.0346	0.055836	-0.07925
	(-1.176)	(1.660)**	
Average	**-0.05989**	**0.120844**	**-0.0959**
All Stocks	-0.05969	-0.03179	-0.00016
	(-3.476)*	(-2.908)*	

Notes to Table 5.5:

The coefficients $\bar{b}_0$ and $\bar{b}_1$ reported in Table 7 are obtained from equation: $r_{it} = a_i + b_{0,M} r_{M,t} + b_{1,M} r_{M,t-1} + b_{0,SMB} SMB_t + b_{1,SMB} SMB_{t-1} + b_{0,HML} HML + b_{1,HML} HML_{t-1} + e_{i,t}$ that was estimated for each year and each stock in each sub-sample separately. SMB is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and HML is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks. This provided estimates of α_i, b_0, b_1, for each stock, each year, and each sub-sample, and each factor. Then, $\bar{b}_0$ and $\bar{b}_1$ were calculated as the averages of b_0 and b_1.

Table 5.6 reports the results regarding the magnitude of the factor contribution. As discussed earlier, when the average sensitivity to the lagged factor is positive ($\bar{b}_1$>0) the contribution of the factor reactions to contrarian profits is due to underreaction. The term $-\hat{\delta}\sigma_f^2$ (where f = M, SMB, HML), i.e. the product of the cross-sectional covariance of contemporaneous and lagged betas with the variance of the factor provides an estimate of the part of contrarian profits due to common factor reactions (underreaction in this case). Note that it is relatively small for the full sample for all factors (0.0041, -0.0377, 0.0001 for the market, SMB and HML factors, respectively). However, this is not the case when other sub-samples are examined. For example, the estimate of the part of contrarian profits due to the SMB factor reactions for the small stocks sub-sample is 0.3035, for the medium stocks sub-sample is 0.2159, etc. The estimate of the part of contrarian profits due to the HML factor reactions for the smallest stocks sub-sample is 0.1364, for the small stocks sub-sample is 0.0977, etc. The contribution of the market factor to contrarian profits is higher for the large, medium, and small stocks than for the largest or smallest stock sub-samples. However, for the other two factors, the estimate of the part of contrarian profits grows larger as one moves from the largest to the smaller stock sub-samples. This suggests that underreaction to the SMB and HML factors contributes less to the contrarian profits of large firms and more to the contrarian profits of medium to small firms.

The negative of the average autocovariance of the error term, -Ω, [$\Omega \equiv \frac{1}{N}\sum_{i=1}^{N} \mathrm{cov}(e_{i,t}, e_{i,t-1})$], that provides an estimate of contrarian profits due to firm-specific overreaction to information is very large (0.3182) for the all-stock group. Note also that it grows smaller as one moves from the largest stock sub-sample to the smallest stock sub-sample, suggesting that overreaction to firm-specific information contributes more to the contrarian profits that are associated with large firms, and less to the contrarian profits that are associated with small firms. For example, for the smallest stock sub-sample -Ω is 0.3479 while for the largest stock sub-sample it is 0.6059, and it might be the case that this unexpected result is related to the thin trading problem (as shown later) which when present does not only affect the estimation of the betas, but the residuals as well, and thus Ω. The negative of the cross-sectional variance of expected returns ($-\sigma_a^2$) provides an estimate of the profits that are not due to the previous terms and is very small for the full sample (-0.00962) suggesting little unexplained contrarian profits.

Table 5.6
Decomposition of contrarian profits

	$-\hat{\delta}\sigma_M^2$ x10^3	$-\hat{\delta}\sigma_{SMB}^2$ x10^3	$-\hat{\delta}\sigma_{HML}^2$ x10^3
Smallest Stocks	0.589517	0.194558	0.136409
Small Stocks	0.710813	0.303474	0.097716
Medium Stocks	0.623599	0.215853	0.091264
Large Stocks	0.759763	0.167253	0.043146
Largest Stocks	0.438937	0.089247	0.072972
All Stocks	0.004146	-0.03767	0.00015

	$-\Omega$ x10^3	$-\sigma_a^2$ x10^3
Smallest Stocks	0.347943	-0.13537
Small Stocks	0.384372	-0.11878
Medium Stocks	0.503950	-0.10204
Large Stocks	0.490321	-0.07987
Largest Stocks	0.605887	-0.06478
All Stocks	0.318222	-0.00962

Notes to Table 5.6:

The term $-\hat{\delta}\sigma_M^2$ provides an estimate of the part of contrarian profits due to market reactions. The term $-\hat{\delta}\sigma_{SMB}^2$ provides an estimate of the part of contrarian profits due to reactions to the size factor, while the term $-\hat{\delta}\sigma_{HML}^2$ provides an estimate of the part of contrarian profits due to reactions to the book-to-market factor. The negative of the average autocovariance of the error term, Ω, defined as $\Omega \equiv \frac{1}{N}\sum_{i=1}^{N} \text{cov}(e_{i,t}, e_{i,t-1})$, provides an estimate of contrarian profits due to overreaction to firm-specific information. The negative of the cross-sectional variance of expected returns ($-\sigma_a^2$) provides an estimate of the profits that are not due to the previous terms.

In order to account for possible biases in the above results coming from time variation in factor sensitivities, contrarian profits are decomposed as described in equations (5.16)-(5.19), as clearly explained in section 5.3. To create the firm specific related factor θ_t, the estimated residuals from the three-factor model in equation (5.20) are employed, as described in (5.17). Table 5.7 (Panel A) presents the slope coefficient estimates: α_1, α_2, and α_3, that give the contrarian profits due to the reactions to the market, SMB and the HML factors respectively. For the market factor (α_1), they are statistically insignificant with the exception of the slope estimates in the small stock sub-sample. For SMB (α_2) they are significant for the smallest, small and largest sub-sample. For HML (α_3) they are significant for the large sub-sample and the all-stock group. The estimates of γ (overreaction to firm-specific information) are statistically significant for the two smallest sub-samples and for the all-stock group, which indicates that firm specific reaction might be responsible for a large part of those groups profits. This is true, for example as can be seen in Panel B, the estimate of contrarian profits due to firm-specific overreaction for the all-stocks group, is approximately 0.2852. Since the average weekly contrarian profit is 0.26, the contrarian profits due to firm-specific overreaction for all-stocks are 110% (0.2852 / 0.26), and they are slightly higher than for JT that find for the same group a contribution equal to 104%. In addition, the term $\alpha_1\sigma^2_M$ (estimate of contrarian profits due to market factor reaction) for the same group is approximately -8%, and it is much smaller compared to the 4% contribution that JT find. Note also, that the HML factor contributes about 37% of contrarian profits while the SMB factor contributes another 8% of profits, and probably explain part of the difference in the results. The SMB and HML factors are not considered by JT, and this can lead, as explained earlier, to more and false structure in the firm specific component, thus misleading them to believe that the firm specific component is responsible for a larger portion of contrarian profits in the absence of the two additional factors. Here for example the magnitude of the bias would be about 45%, since that much would be missing had the two factors been excluded (37% from HML and 8% from SMB). This would have an effect on residuals and hence the firm specific component[98].

To summarize, most contrarian profits are due to firm-specific information. Not including the FF factors would bias our results, consistent with our initial suggestion that excluding the factors imposes false structure on residuals, since their addition removes about 45% of the profits previously considered to be due to the firm specific component. An interesting finding is that although, on average, stocks react with a delay to common factors, most of the contrarian profits are due to overreaction to firm-specific information; the lead-lag reaction contributes very little to contrarian profits. One explanation for this is that it might be related (in our case) to the bias introduced to the beta estimates from thin trading (Clare et al. 2002). Based on this suggestion and our earlier findings of thin-trading effects on profits, the tests are next repeated using the sample of frequently traded firms, adjusted for thin trading with an OLS AR(1) model, in order to quantify the possible effect of thin trading.

[98] For example, tests are repeated using equation (5.18) with only the market factor: $\pi_t = \alpha_0 + \alpha_1 (r_{M,t-1} - \bar{r}_M)^2 + \gamma\theta_{t-1} + u_t$. The contribution to contrarian profits from firm-specific overreaction for all-stocks is then equal to 140%, about 36% higher than JT and 31% higher than our results with the three-factor version. Thus, false structure is imposed on the firm specific component by omitting the two factors. See Appendix, section 5.6.1.1 for details.

Table 5.7
Decomposition of contrarian profits with time-varying factor sensitivities

Panel A: Estimated coefficients					
	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\alpha_2 \times 10^3$	$\alpha_3 \times 10^3$	$\gamma \times 10^3$
Smallest Stocks	-0.22073 (-1.379)	-33.67462 (-1.296)	-87.19594 (-2.363)*	-32.81700 (-0.558)	70.39618 (3.412)*
Small Stocks	-0.30858 (-1.504)	94.35638 (2.834)*	-123.76790 (-2.617)*	59.75606 (0.792)	88.06031 (3.330)*
Medium Stocks	0.01066 (0.061)	15.41389 (0.547)	16.89697 (0.422)	27.50733 (0.431)	34.50854 (1.543)
Large Stocks	0.25049 (1.435)	19.33992 (0.683)	-56.79616 (-1.412)	253.60950 (3.954)*	0.27587 (0.012)
Largest Stocks	-0.08006 (-0.169)	-59.92972 (-0.781)	585.70009 (5.375)*	71.87237 (0.414)	32.01471 (0.526)
All Stocks	-0.15717 (-1.529)	-10.33301 (-0.641)	14.08264 (0.596)	103.22807 (2.724)*	54.43379 (4.119)*

Panel B: Factor contributions to contrarian Profits				
	$\alpha_1\sigma_M^2 \times 10^3$	$\alpha_2\sigma_{SMB}^2 \times 10^3$	$\alpha_3\sigma_{HML}^2 \times 10^3$	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}) \times 10^3$
Smallest Stocks	-0.066727 [2.03595]	-0.128067 [3.90754]	-0.030218 [0.92200]	0.368825 [-11.25340]
Small Stocks	0.186970 [0.71599]	0.024822 [-0.69612]	0.055024 [0.21071]	0.461372 [1.76679]
Medium Stocks	0.0305432 [0.10559]	0.024817 [0.08580]	0.025329 [0.08757]	0.180800 [0.62507]
Large Stocks	0.038322 [0.08591]	-0.083418 [-0.18700]	0.233526 [0.52349]	0.001445 [0.00324]
Largest Stocks	-0.118753 [-0.13106]	0.860238 [0.94940]	0.066181 [0.07304]	0.167734 [0.18512]
All Stocks	-0.020475 [-0.07946]	0.020684 [0.080274]	0.095053 [0.36890]	0.285194 [1.10685]

Notes to Table 5.7:

The coefficients α_0, α_1, α_2, α_3 and γ are obtained from the decomposition of contrarian profits, in equation (5.18), where θ is described by equation (5.17), and is created by the residuals estimated from equation (5.20).The estimate of the contrarian profits due to delayed reactions to the common factor is given by the product of the α's and the variance of the relevant common factor ($\alpha_i\sigma_F^2$), while an estimate of contrarian profits due to overreaction is given by (5.19). Numbers in bracket are ratios of each component relative to the average contrarian profit from Table 5.3. Profit contributions do not add up to a 100% due to estimation errors. t-statistics appear in parentheses. * denotes significance at the 5%; ** denotes significance at the 10% level.

5.4.1. Infrequent and/or thin trading

The operation of trading in the ASE (no market makers, computerized trading, etc) excludes bid-ask biases as possible explanations of results so far, as has been discussed. However, there might be stocks that trade infrequently and/or trade thinly, and results so far may be partly due to such market frictions. This subsection, in order to investigate whether this is indeed the case, repeats the analysis for a sample that trades frequently and is adjusted for thin trading.

Results from estimating equation (5.20) for the adjusted sample[99] are presented in Tables 5.8 & 5.9. Table 5.8, shows that contrary to earlier results, reactions to all factors are stronger to contemporaneous than to lagged factor realizations. For example, the average slope coefficient on the contemporaneous market factor is 0.9773 while the average beta on the lagged market factor is -0.0184. The average slope coefficient on the lagged SMB factor is 0.1135 while on the contemporaneous SMB factor it is 0.1905. Furthermore, the cross-sectional covariance is negative ($\delta < 0$) for all sub-samples and all three factors (except for the HML factor in the some cases, and SMB for the all-sample group), which indicates that reactions to all three factors could contribute positively to contrarian profits in the ASE, in most cases. Although common factors can contribute positively for both the adjusted and unadjusted for thin trading samples, there are differences in the slope coefficients; stock reactions to the current (lagged) common factor are now much stronger (weaker).

[99] This infrequent and thin trading adjusted sample is defined as in Section 5.2.3.1 and footnote 87. the reported results are based on adjustments with an OLS AR(1) model. The results based on thin trading adjustments with a Recursive OLS AR(1) model are similar and not reported, however they are available in the Appendix (section 5.6.3) Tables 5.25 to 5.27.

Table 5.8
Average estimates of stock return sensitivities to factor realizations
(Sample adjusted for infrequent and thin trading)

Market Factor	$\bar{b}_{o,M}$	$\bar{b}_{1,M}$	$\hat{\delta}_M$
Smallest Stocks	1.02533	0.002140	-0.098554
	(25.523)*	(0.083)	
Small Stocks	0.927316	-0.015891	-0.087932
	(21.324)*	(-0.596)	
Medium Stocks	1.00995	-0.024807	-0.106662
	(26.164)*	(-0.946)	
Large Stocks	1.002399	-0.025706	-0.067694
	(29.271)*	(-1.022)	
Largest Stocks	0.92166	-0.027877	-0.043612
	(33.542)*	(-1.593)	
Average	**0.977331**	**-0.0184282**	**-0.080891**
All Stocks	0.981573	0.082092	-0.011728
	(49.136)*	(8.220)*	

SMB	$\bar{b}_{o,SMB}$	$\bar{b}_{1,SMB}$	$\hat{\delta}_{SMB}$
Smallest Stocks	0.424822	0.353369	-0.273707
	(8.758)*	(6.691)*	
Small Stocks	0.297950	0.180668	-0.106702
	(7.834)*	(4.194)*	
Medium Stocks	0.197736	0.09165	-0.050027
	(5.974)*	(2.443)*	
Large Stocks	0.082194	0.014231	-0.005237
	(3.112)*	(0.435)	
Largest Stocks	-0.049796	-0.072417	-0.022801
	(-2.375)*	(-2.753)*	
Average	**0.190581**	**0.113500**	**-0.091695**
All Stocks	0.159736	0.392709	0.024829
	(12.347)*	(16.379)*	

HML	$\bar{b}_{o,HML}$	$\bar{b}_{1,HML}$	$\hat{\delta}_{HML}$
Smallest Stocks	0.066513	-0.042120	0.081943
	(1.385)	(-0.958)	
Small Stocks	0.060843	-0.070945	0.012444
	(1.429)	(-1.936)**	
Medium Stocks	-0.024942	-0.052442	-0.00228
	(-0.596)	(-1.558)	
Large Stocks	-0.011536	-0.096043	0.009946
	(-0.343)	(-3.049)*	
Largest Stocks	-0.025213	-0.011321	-0.003465
	(-0.835)	(-0.503)	
Average	**0.013133**	**-0.054574**	**0.019718**
All Stocks	-0.043867	-0.036862	0.000309
	(-2.698)*	(-3.300)*	

Notes to Table 5.8:

See Notes to Table 5.5.

This is consistent with the finding of Clare et al. (2002) that betas are sensitive to thin trading. Hence, betas would be biased had thin trading not been considered, and estimated residuals would be affected as well, having further structure added to them that is not there. The last, would bias the findings for the firm specific component contribution, and the extent of this bias can be seen in Table 5.9.

Table 5.9 reports the results as regards the magnitude of the contribution of each factor. The average sensitivity to the lagged factor is again relatively small for the all-stock sample for all factors (0.02324, -0.0365, -0.0003 for the market, SMB and HML factors, respectively), but as for the non-adjusted sample, this is not the case when the size sub-samples are examined; however the overall magnitudes related to common factor contribution are now smaller than before. For example, the estimate of the part of contrarian profits due to the market factor reactions for the medium stock sub-sample is 0.2114 compared to 0.6236 in Table 5.6, and for the smallest stocks sub-sample is 0.1953 compared to 0.5895. As can clearly be seen, there is an effect on the common factor contributions, which is due to the presence of firms that trade thinly and inflate the lag part of the lead-lag relationship.

The negative of the average autocovariance of the error term, that provides an estimate of contrarian profits due to overreaction to firm-specific information, is 0.4601 for the all-stock group, and larger than for the unadjusted sample where it was 0.3182 (Table 5.6). This is not the only difference in the two samples. The most important difference is that now -Ω grows monotonically larger as one moves from the largest stock sub-sample (0.2706) to the smallest stock sub-sample (0.6177), suggesting that overreaction to firm-specific information contributes more to the contrarian profits associated with small firms, and less to the contrarian profits associated with large firms. Thus, not only the betas, but also the firm specific reaction is affected by thin trading, and results are misleading if the sample is not treated for the problem. Furthermore, results are now consistent with the JT findings, and closer to the expectation that smaller firms are more prone to such strategies since they are followed by less investors and suffer from larger information asymmetries (Kang et al. 2002). The estimate of profits that are not due to the previous terms ($-\sigma_a^2$) is very small for the all-stock sample -0.0035, and similar to the unadjusted sample (Table 5.6) suggesting few unexplained contrarian profits.

Table 5.9
Decomposition of contrarian profits
(Sample adjusted for infrequent and thin trading)

	$-\hat{\delta\sigma}_M^2 \text{ x}10^3$	$-\hat{\delta\sigma}_{SMB}^2 \text{ x}10^3$	$-\hat{\delta\sigma}_{HML}^2 \text{ x}10^3$
Smallest Stocks	0.195288	0.402003	-0.075454
Small Stocks	0.174240	0.156717	-0.011459
Medium Stocks	0.211354	0.073476	0.002099
Large Stocks	0.134138	0.007691	-0.009158
Largest Stocks	0.086419	0.033488	0.003191
All Stocks	0.023239	-0.036467	-0.000284
	$-\Omega \text{ x}10^3$	$-\sigma_a^2 \text{ x}10^3$	
Smallest Stocks	0.617664	-0.095402	
Small Stocks	0.565036	-0.133599	
Medium Stocks	0.506189	-0.088213	
Large Stocks	0.442875	-0.063274	
Largest Stocks	0.270597	-0.04419	
All Stocks	0.460082	-0.003519	

Notes to Table 5.9:

See notes to table 5.6.

Table 5.10 (Panel A) presents the slope coefficient estimates of equation (5.18). The market factor (α_1) is now significant for the large firms and the full sample, instead of the small firms in the untreated sample. Coefficient (α_2) related to SMB is now significant only for the full sample, while HML (α_3) is still significant for the all-stock sample, but now instead of the large sample it is significant for the largest sample. The estimates of γ (overreaction to firm-specific information) are still statistically significant for the all-stock sample, but now the large firms are affected by this factor instead of the two smaller groups in the case of the untreated for thin trading sample. The two smaller samples are probably affected by other factors than the ones included in this model, since the constant coefficient estimates are statistically significant for both of them. As can be seen again, the two FF factors provide additional information especially for the full sample. This is consistent with the chapter's suggestion on the multi-factor model superiority (excluding SMB & HML in this second stage (equation 5.18) would lead to the misperception of a large amount of profits as been related to the firm specific component, where of course the factors are significant). The evidence is clearer in Panel B where the magnitude of the contribution of each factor is observed. The estimate of contrarian profits due to firm-specific overreaction for the all-stocks sample is 0.1989, and since the average weekly contrarian profit is 0.3962 (Table 5.3, Panel E), the contrarian profits due to firm-specific overreaction for all-stocks are about 50% (0.1989/0.396). All common factors together explain about 50%, of which 15% comes from the market factor, while about -18% and 17% come from the SMB and HML factor respectively. The figures however are quite different compared to the earlier ones for the unadjusted sample. For example, the firm specific contribution is more than 50% smaller. This last figure shows that by considering thin trading, some of the structure in the residuals of equation (5.20) related to the effect on betas earlier discussed has been removed, and thus the firm specific component contribution is reduced.

To summarize for this sub-section, when the sample is adjusted for market frictions results change, because the bias from the betas is removed, and firms react stronger to the contemporaneous factor. Considering constant factor sensitivities, overreaction to firm-specific information contributes more to the contrarian profits associated with small firms, and less to the contrarian profits associated with large firms, and there are much smaller unexplained contrarian profits. Allowing for changes in factor sensitivities shows that smallest and small firms behaviour is affected by other factors than the ones considered in the model, consistent with the literature that finds firms of this size to have a behaviour that is difficult to explain with factor models (Fama 1998). JT find that for the well-developed US market thin trading does not change results significantly, however this is not the case for other markets (UK Clare et al. 2002), and especially less developed markets like the ASE. It is thus crucial that all studies for such markets try to take into account for market frictions to make certain that their findings are reliable. It can certainly be argued (given the subsection's evidence) that for the specific case of the ASE, not considering thin trading would have biased the results, overstating (understating) firm specific (common factors) contributions.

Table 5.10
Decomposition of contrarian profits with time-varying factors
(Sample adjusted for infrequent and thin trading)

Panel A: Estimated coefficients

	α_0 x 10^3	α_1 x 10^3	α_2 x 10^3	α_3 x 10^3	γ x 10^3
Smallest Stocks	0.39355 (1.977)*	17.73890 (0.606)	-17.99186 (-0.441)	25.25116 (0.368)	33.33074 (1.089)
Small Stocks	0.40085 (1.769)**	27.28584 (0.819)	28.19609 (0.608)	90.69585 (1.160)	22.98898 (0.660)
Medium Stocks	0.23340 (1.392)	-0.17025 (-0.007)	43.62574 (1.272)	5.16421 (0.089)	7.52694 (0.292)
Large Stocks	0.03474 (0.289)	-40.27844 (-2.277)*	-20.41131 (-0.829)	-3.59836 (-0.087)	91.07125 (4.923)*
Largest Stocks	0.07605 (0.552)	29.68204 (1.465)	-9.21255 (-0.327)	78.12983 (1.645)**	28.47256 (1.344)
All Stocks	0.14116 (1.603)	30.05411 (2.284)*	-48.16093 (-2.618)*	72.47863 (2.380)*	37.21462 (2.772)*

Panel B: Factor contributions to contrarian Profits

	$\alpha_1\sigma_M^2$ x 10^3	$\alpha_2\sigma_{SMB}^2$ x 10^3	$\alpha_3\sigma_{HML}^2$ x 10^3	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10^3
Smallest Stocks	0.035150 [0.05453]	-0.026425 [-0.04100]	0.023251 [0.03607]	0.178183 [0.27644]
Small Stocks	0.054068 [0.11905]	0.041413 [0.09118]	0.083514 [0.18388]	0.122897 [0.27060]
Medium Stocks	-0.000337 [-0.00099]	0.064075 [0.18822]	0.004755 [0.01397]	0.040238 [0.11820]
Large Stocks	-0.079813 [-0.19626]	-0.029979 [-0.07372]	-0.003313 [-0.00815]	0.486860 [1.19715]
Largest Stocks	0.058816 [0.17214]	-0.013531 [-0.03960]	0.071943 [0.21056]	0.152212 [0.44549]
All Stocks	0.059553 [0.15031]	-0.070736 [-0.17854]	0.066739 [0.16845]	0.198946 [0.50214]

Notes to Table 5.10:

See Notes to table 5.7.

5.4.2 Single factor models

Section 5.3 revealed that the FF factors describe our dataset better than the single-factor model suggested by JT and others. To measure however the possible effect that this might have on the results, the analysis is performed using a single factor model this time. As can be seen in the Appendix section 5.6.2.1 (with a detailed analysis of the findings), the single-factor model results are very different from those of the multifactor model. In Table 5.13, the estimated betas are higher for the lagged factor than for the current one, and the contribution of the market (firm specific) factor is higher for smaller firms (larger firms). In Table 5.14 where time-varying factor sensitivities are considered, there are still a lot of unexplained profits.

The above results are in some cases similar to the ones observed for the full sample, and consequently they might not be related to the use of a single-factor model, but to the fact that thin trading has not been considered. However, looking to the relevant tables of both sections with treated data and comparing them, it is obvious that the use of one factor instead of three does contribute to the further distortion of results. This can be seen by comparing average betas (both current and lagged) in Tables 5.8 and 5.13. To decide on this one can also be assisted by sections *5.6.2.2, to 5.6.2.4* (in the Appendix) where tables for single-factor analysis are presented (Tables 5.15 to 5.20) using respectively: frequently trading firms AR(1) and AR(1) recursive thin trading adjusted returns as described in subsection *5.2.3.1.*

There is always the chance however, that part of the single-factor model failure is related to the factor employed, and might improve if another factor was used in place of the ASE GPI. To this end, the thesis retests using an equally-weighted index (Appendix, section 5.6.2.5 with tables and detailed analysis) instead of the ASE value-weighted index, following Ikenberry et al. (1995) that use CRSP equal- and value-weighted indices among other benchmarks, and also based on Chopra, Lakonishok & Ritter (1992) who find sensitivity of results on the index used. Michaely, Thaler & Womack (1995) also use four different proxies for the Market portfolio, to investigate among other things whether an equally-weighted index delivers different results from a value-weighted index, but they find very small differences. Here, the same is done (not for a well-developed market however), but consistent with the last study, results indicate that although betas change (becoming larger for current and smaller for lagged factors), the other problems still exist. For example, firm specific contribution for constant factor sensitivities still grows, as one moves from smaller to larger firms, and the magnitude is now even larger. In addition, the portion of unexplained contrarian profits for varying factor sensitivities is still large. It can thus be concluded that the main reason for the failure of the single-factor model to explain returns and profits, is unrelated to the index used.

Literature has shown however, that contrarian profitability and stock market overreaction might be affected by the month of January, and this might be driving force behind the inferiority of the single-factor model. For example Jegadeesh (1990) finds abnormal returns of 4.37% in January and only 2.2% for all other months together. Pettengill & Bradford (1990) find that two-thirds of contrarian abnormal returns come in January. Zarowin (1990) shows that there is no overreaction out of January after controlling for size. Based on the above suggestions, and on recent evidence of a turn-of the year effect in ASE (Spyrou 1998), the chapter searches whether the anomaly is behind findings and affects single-factor models, before putting the coffin nail to them.

As can be seen in the Appendix (section 5.6.2.6 with relevant tables and a detailed analysis) the January effect, does not influence contrarian profits and does not alter their decomposition. This is consistent with DeBondt and Thaler (1987) and with Claire & Thomas (1995) who also test for seasonal effects, and find that the overreaction effect is other than the January effect since abnormal returns for contrarian strategies are also observed out of January. Results are also in line with Richards (1997) who finds that only 5% of the total 23.1% of the abnormal returns belong to January. The only difference with this section's results is related to the common factor, whose contribution is still very small but is related to overreaction here. This is consistent with JT's suggestion that the contribution of the market factor is very small (a further justification for using the FF factors). This section further contributes to JT discussion with Lo and Mackinley on the particular issue by showing that even the small underreaction to the market factor is restricted to the month of January.

To summarise, results are problematic for the single-factor model even when thin trading, alternative factors, or the January seasonal are considered. This shows that the single-factor model problems are probably related to risk miss measurement that the chapter tackles by using the FF more relevant factors.

5.5 Conclusion

This chapter investigates the existence of short-term contrarian profits and the sources of such profits for the Athens Stock Exchange. A three-factor model is used for the decomposition of these profits to their various sources, motivated from the Fama and French (1993, 1996) three-factor model. As this is an emerging market, judgment is also passed on whether market frictions give false impressions of return predictability. Furthermore, several specifications of returns are employed to consider the difference on the results before and after taking in to account for risk.

The chapter finds that individual stock returns in the ASE are negatively serially correlated, and this leads to statistically significant contrarian profits that are not due to market frictions or risk. The profits for the smallest firms are much higher than the profits for other size sub-samples and appear to reduce gradually as one moves to larger stock sub-samples (when thin-trading is considered) consistent with the findings of Lo and Mackinley (1990) and JT. This is also consistent with expectations that smaller firms should be more prone to such strategies since they are followed by less investors and suffer from larger information asymmetries (Kang et al. 2002). Furthermore, firm-specific overreaction contributes more to the contrarian profits associated with small firms, and less to the profits associated with large firms. A lot of information is added with the SMB and HML factors that explain a large part of profits that under the JT model would be considered as firm specific.

More specifically, the chapter shows that the FF factors are related to contrarian profits, while the market factor is unrelated, and thus these FF factors are used for the decomposition. Furthermore, comparing single and multifactor models, the later are found to be superior, even when an equally-weighted index, or thin trading and seasonality are considered.

This section of the thesis also shows the need to take into account for thin trading, given that it affects results especially regarding the decomposition of profits. For example, when all firms available are used, results indicate that equity returns react strongly to lagged market factors and less strongly to contemporaneous market factors, contrary to thin trading adjusted results. In addition, overreaction to firm-specific information contributes more to the contrarian profits associated with large firms and less to the contrarian profits associated with small firms for the full sample, contrary again to thin trading adjusted results. When the assumption of constant common factor sensitivities through time is dropped, the contribution of the common factors does not change significantly, but the contribution of the firm specific component is exaggerated compared to when thin trading adjusted results are used.

To summarize, the main results that emerge from the analysis are as follows:

- Serial correlation is present in the ASE, and it leads to short-run contrarian profits, in addition to longer-term profits observed in the previous chapter.

- Contrarian profits persist even after adjusting for risk and for market frictions. However, because a portion of the profits is explained by the above, and the decomposition is biased if the sample is not adjusted for market frictions, one must always try to do so, especially for developing markets.
- The results are robust even when allowing for time variation in factor sensitivities.
- Results become consistent with findings for the US market, in the sense that contrarian profits decline as one moves from smaller stocks to larger ones when accounting for market frictions.
- The FF factors add a lot of information and improve the model, and increase (decrease) the common factor (firm specific) component contribution. The superiority of the multifactor model, is visible from the fact that the contribution to profits from firm-specific reaction are not higher than the contribution of common factors like in the JT study, but they are about equal when using the FF factors.
- The negative loadings observed for the largest and large firms for the SMB factor and the HML factor, are consistent with Fama and French arguments. However, the FF factors fail to completely explain over-and underreaction and the profitability of contrarian strategies in ASE, either because part of the contrarian profits are truly genuine, or because the model is itself only an incorrect representation of reality as Davis Fama and French (2000) state.

This chapter further contributes to literature by:

- Providing short-term evidence on contrarian profits for the first time in the ASE
- Decomposing contrarian profits by applying the JT strategy to ASE for the first time
- Considering changes in size by annual rebalancing stocks, improving on JT Methodology
- Removing the bias that is introduced by JT where only stocks that exist at the beginning of the period are held
- Showing that the single-factor model used by JT with the Market factor, is not appropriate (at least for ASE), since profits are unrelated to it
- By further showing that profits are more related to the FF factors and introducing this model to the strategy
- By using FF risk adjusted returns to create contrarian profits, since investors would be interested risk adjusted returns
- By taking into account for well documented anomalies such as seasonal effects that JT do not
- By using an improved methodology compared to JT to account for thin trading compared to the skip a day method, which is criticized in the area of contrarian strategies (see for example Conrad & Gultekin 1997), and that is also why Lo and Mackinley (1990) avoid the skip a day method.

To summarize, for efficient results one needs to take into account for market frictions and use a multifactor model with factors relevant to profits. However, although overall the three-factor model is better than the single-factor model, contrarian profits are still present even when this model is used to account for more risk premiums. There are perhaps other factors at work that are not captured (especially for smallest and large firms) as Davis Fama and French (2000) admit, or there are genuine contrarian profits. Even if this is not the case however, the unexplained part of the contrarian profits can be related to the fact that the three-factor model although valid for large and well-developed capital markets, may not be entirely true for markets like the ASE (although it represents reality better). Thus, before the thesis concludes that there are genuine contrarian profits, it will perform tests in the next chapter using a larger and well-developed market, and it will contrast results with the ones for the developing market of Greece. If results hold for both markets and if they are similar, then it could be suggested that, having controlled for the most known risk factors and having taken consideration for market frictions, profits are genuine as far as the idiosyncrasies of a developing market are concerned.

5.6 Appendix

5.6.1 Results without the additional factors in the time varying parameters section

In this section, the same samples as in the main body of the chapter are considered, namely, the full sample and the thin trading adjusted sample. There is no difference up to the point of the time-varying factor sensitivities analysis, more specifically the difference is that instead of equation 5.18 as presented in section 5.3, the JT version is used (described in the same section).

5.6.1.1 For the Full sample

Results allowing for time-variation in factor sensitivities, are presented in Table 5.11. The slope coefficient estimates (α_l), are statistically insignificant with the exception of the slope estimates in the small stock sub-sample. However, the estimates of γ are statistically significant for all sub-samples except one (the large stock sub-sample). The estimate of contrarian profits due to firm-specific overreaction for the all-stocks sample, is approximately 0.364104. Since the average weekly contrarian profit is 0.26, the contrarian profits due to firm-specific overreaction for all-stocks are 140% (0.364104 / 0.26). Also, the term estimate of contrarian profits due to common factor reaction is approximately -0.01145, indicating that contrarian profits due to common factor under-reaction for the all-stock sample are - 4.4%.

Table 5.11
Decomposition of contrarian profits with a single factor only for time-varying factor sensitivities (instead of eq. 5.17)

	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\gamma \times 10^3$	$\alpha_1 \sigma_M^2 \times 10^3$	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}) \times 10^3$
Smallest Stocks	-0.2831 (-1.802)**	-36.0946 (-1.389)	54.8366 (2.791)*	-0.07152 [2.1712]	0.317738 [-9.69575]
Small Stocks	-0.34407 (-1.707)**	94.92038 (2.847)*	72.5095 (2.877)*	0.188071 [0.72019]	0.420140 [1.60886]
Medium Stocks	0.03329 (0.196)	16.6781 (0.595)	38.8233 (1.83)**	0.033045 [0.114224]	0.224953 [0.77771]
Large Stocks	0.34702 (2.00)*	28.1048 (0.982)	7.04012 (0.325)	0.055686 [0.12483]	0.040792 [0.09128]
Largest Stocks	0.26476 (0.558)	-49.2615 (-0.628)	127.399 (2.15)*	-0.0976 [-0.10771]	0.738188 [0.81469]
All Stocks	-0.09878 (-0.978)	-5.7770 (-0.358)	62.8387 (4.982)*	-0.01145 [-0.04402]	0.364104 [1.400402]

Notes to Table 5.11:

See Notes to Table 5.10

An interesting finding is that although stocks react with a delay to common factors most of the contrarian profits are due to firm-specific information overreaction. For example, we report here that over 140% of the profits are due to firm-specific information, while the delayed reaction contribution is close to zero. This implies that about -40% should be accounted for by cross-sectional differences in unconditional expected returns, which seems large particularly given that α_0 is insignificant. However, when we use the three common factors instead of the single factor in (5.18), this problem is no longer present, and this is further evidence of the superiority of the multifactor model against the single factor model.

5.6.1.2 For the Thin-Trading adjusted sample

Table 5.12 presents the results for equation (5.18) using the JT version on the thin-trading adjusted sample. The slope coefficient estimates (α_l) are statistically significant only for the all stocks sample and the large stock sub-sample, while the estimates of γ are statistically significant for the all stocks sample, and the large and largest stock sub-sample. The estimate of contrarian profits due to firm-specific overreaction for the all-stocks sample, is 0.202438. Since the average weekly contrarian profit is 0.3962 (Table 5.3, Panel E), the contrarian profits due to firm-specific overreaction for all-stocks are 51% (0.202438 / 0.3962). Also, the term $\alpha_l\sigma^2_M$ (estimate of contrarian profits due to common factor reaction) is approximately 0.061351, indicating that contrarian profits due to common factor under-reaction for the all-stock sample are 15%. The magnitudes of the contributions are quite different compared to the ones for the unadjusted sample, the common factor contribution is now positive and larger, and the firm specific contribution is about three times smaller from 140% that it was. The same picture holds for the sub-samples. This shows that by considering thin trading for the single factor analysis as well, we have removed some of the structure in the residuals of equation (5.20) related to the effect on betas we spoke about earlier.

When we include the additional two factors, we explain about 35% more of the contrarian profits, 18% of which comes from the SMB factor and 17% from the HML factor. In addition, the constant estimate is now much smaller. All these indicate that the three factor analysis is much more efficient than the single factor analysis, even if we do the first part of the analysis (relevant to constant factor sensitivities in (5.20)) with the FF model and differentiate in the second part of the analysis (relevant to (5.18)) employing one factor.

Table 5.12
Decomposition of contrarian profits with a single factor only for time-varying factor sensitivities (instead of eq. 5.17)
(Sample adjusted for infrequent and thin trading)

	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\gamma \times 10^3$	$\alpha_1\sigma_M^2 \times 10^3$	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}) \times 10^3$
Smallest Stocks	0.3892 (1.992)*	18.082 (0.621)	33.3609 (1.133)	0.035828 [0.0556]	0.178544 [0.277]
Small Stocks	0.4527 (2.032)*	31.2180 (0.941)	-10.5749 (-0.315)	0.061854 [0.1362]	-0.056595 [-0.1246]
Medium Stocks	0.267 (1.619)	1.2751 (0.052)	13.8048 (0.556)	0.002526 [0.0074]	0.073882 [0.2170]
Large Stocks	0.0186 (0.158)	-40.995 (-2.329)*	88.02093 (4.942)*	-0.081226 [-0.1997]	0.47108 [1.1584]
Largest Stocks	0.0964 (0.711)	32.0956 (1.589)	34.7250 (1.699)**	0.063593 [0.1861]	0.185845 [0.5439]
All Stocks	0.1321 (1.516)	30.9639 (2.34)*	37.8253 (2.891)*	0.061351 [0.1548]	0.202438 [0.5109]

Notes to Table 5.12:

t-statistics appear in parentheses.
* indicates significance at the 5% level; ** indicates significance at the 10% level
Numbers in bracket are ratios of each component relative to the average contrarian profit from Table 5.3 (Panel D). Profit contributions do not add up to a 100% due to estimation errors

5.6.2 Single-Factor Model Results

5.6.2.1 Decomposition of profits

Trzcinka (1986) suggested that most of the risk that affects asset movements can be captured by one factor. Here we use a single factor model, consistent with JT. The rest of the methodology is the same, the only thing that changes is that we estimate a simple version of equation (5.10) using one common factor:

$$r_{it} = a_i + b_{0,i} r_{M,t} + b_{1,i} r_{M,t-1} + e_{i,t} \tag{5.21}$$

where:

r_{it} is the return of stock i at time t,

a_i is the unconditional expected return of stock i,

r_{Mt} is the return on the market portfolio at time t,

$e_{i,t}$ is the estimated residual of stock i at time t, and

$b_{0,i}$ and $b_{1,i}$ are the estimated sensitivities of stock i on the contemporaneous and lagged market returns, respectively.

Results from the empirical estimation of (5.21) appear in Table 5.13 and suggest that, on average, equity returns in the ASE do not fully react contemporaneously to the common factor, but react with a one-week lag. For instance, the average slope coefficient on the lagged (current) factor is 0.57997 (0.25224). Furthermore, this effect is not confined to small firms but it is more pronounced for medium and large firms (0.626449 and 0.636693, respectively).

In fact, it is less pronounced for the smallest stocks than any other sub-sample of stocks[100]. The cross-sectional covariance of contemporaneous and lagged betas ($\hat{\delta}$) is negative for all sub-samples and all stocks, suggesting that common factor reactions could contribute positively to contrarian profits. This is consistent with JT findings for US stocks, however it's not clear which stocks act as lead and which as lag.

The lower part of Table 5.13 reports tests of the magnitude of the contribution of each effect. The term ($-\hat{\delta}\sigma_M^2$) provides an estimate of the part of contrarian profits due to common factor reaction and is relatively small for the full sample (0.003744). However, it grows bigger as we move from the largest stock sub-sample (0.000392) to the smallest stock sub-sample (0.3513), with a peak at the medium stock sub-sample. This suggests that common factor reactions contribute less to the contrarian profits of large firms and more to the contrarian profits of medium to small firms. On the other hand, -Ω, that provides an estimate of contrarian profits due to the reaction to firm-specific information, is quite large for the full sample. However, it grows smaller as we move from the largest sub-sample (0.732611) to the smallest sub-sample (0.04354), suggesting that overreaction to firm-specific information contributes more to the contrarian profits associated with large firms, and less to the contrarian profits associated with small firms. The effect of ($-\sigma_a^2$) is small for the full sample , however, it also grows larger as we move from the largest stocks to the smallest stock sub-sample, suggesting larger unexplained contrarian profits for the smallest firms.

[100] This could be connected to the fact that this sub-sample is the only one with loses in Table 5.3.

Table 5.13
Average estimates of stock return sensitivities to current and lagged market returns & decomposition of contrarian profits (single-factor model)

	$\bar{b}_o$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.13026	0.46724	-0.24548
	(3.830)*	(10.128)*	
Small Stocks	0.22894	0.59910	-0.32699
	(6.216)*	(11.829)*	
Medium Stocks	0.24176	0.62645	-0.32922
	(6.726)*	(12.946)*	
Large Stocks	0.31983	0.63669	-0.34359
	(9.695)*	(11.960)*	
Largest Stocks	0.34499	0.57634	-0.27367
	(10.683)*	(14.983)*	
Average	**0.25224**	**0.57997**	**-0.29972**
All Stocks	0.76166	0.12377	-0.00262
	(34.545)*	(14.002)*	
	$-\hat{\delta}\sigma_M^2$ **x10^3**	**-Ω x10^3**	$-\sigma_a^2$ **x10^3**
Smallest Stocks	0.35130	0.04354	-0.24085
Small Stocks	0.467934	0.222327	-0.19672
Medium Stocks	0.471126	0.44381	-0.14094
Large Stocks	0.000492	0.505366	-0.13139
Largest Stocks	0.000392	0.732611	-0.06526
All Stocks	0.003744	0.143985	-0.00733

Notes to Table 5.13:

The coefficients $\bar{b}_0$ and $\bar{b}_1$ are obtained from equation $r_{it} = a_i + b_{0,i} r_{M,t} + b_{1,i} r_{M,t-1} + e_{i,t}$, which was estimated for each year and each stock in each sub-sample separately. This provided estimates of α_i, b_0, b_1, for each year, each stock in each sub-sample and the full sample as well. Then, $\bar{b}_0$ and $\bar{b}_1$ were calculated as the averages of b_0 and b_1 for each sub-sample and each year. An estimate of the potential contribution to contrarian profits of the differences in the timing of stock price reactions to the common factors is provided by $\hat{\delta}$, which was estimated as: $\hat{\delta} = \frac{1}{N}\sum_{i-1}^{N} E\{(b_{0,i} - \bar{b}_o)(b_{1,i} - \bar{b}_1)\}$. The term $-\hat{\delta}\sigma_M^2$ provides an estimate of the part of contrarian profits due to common factor reactions. The negative of the average autocovariance of the error term, Ω, defined as $\Omega \equiv \frac{1}{N}\sum_{i=1}^{N} \text{cov}(e_{i,t}, e_{i,t-1})$, provides an estimate of contrarian profits due to overreaction to firm-specific information. The negative of the cross-sectional variance of expected returns ($-\sigma_a^2$) provides an estimate of the profits that are not due to the previous two terms.

With regards to time varying factor sensitivities, we now use a simpler version of 5.18 with one instead of three common factors. This is the JT version of 5.18:

$$\pi_t = \alpha_0 + \alpha_1 (r_{M,t-1} - \bar{r}_M)^2 + \gamma\theta_{t-1} + u_t$$

where:

$r_{M,t-1}$ is the return on the market portfolio at time *t-1*,

θ_t is created by (5.17) using e_t estimated from (5.10),

$\bar{r}_M$ is the average common factor return,

The results for time varying factor sensitivities are presented in Table 5.14. The constant coefficient estimates are statistically insignificant with the exception of the large stock sub-sample (*t*-statistic: 2.044). The slope coefficient estimates (α_1), which are related to the contrarian profits due to the common factor reaction, are statistically insignificant with the exception of the slope estimates in the small stocks sub-sample (*t*-statistic: 3.154). However, the estimates of γ, which give the overreaction to firm-specific information, are statistically significant at the 5% level for the whole sample (*t*-statistic: 5.211) and statistically significant at the 10% level for small stocks (*t*-statistic: 1.83).

The estimate of contrarian profits due to firm-specific overreaction for the all-stocks sample is approximately 0.348088. The contrarian profits due to firm-specific overreaction for all-stocks are thus 133.1% (0.348088 / 0.26). Also, the term $\alpha_1\sigma_M^2$, which provides an estimate of contrarian profits due to common factor reaction, is approximately -0.009733 which suggests that contrarian profits due to common factor underreaction for all-stocks are -3.7% (-0.009733 / 0.26). There is a portion of contrarian profits not captured by the model (since these two figures should ad up to one), and thus related to the constant coefficient and other factors that contribute about -30.0%

Looking again at profits growing as we move from smallest to largest firms (Table 5.3, Panel A) we find that it looks suspicious. The larger the firm, the less responsive it should be to contrarian and other trading strategies based on past information, because such firms are followed by more analysts and investors than smaller firms do, and thus their prices reflect faster a larger amount of information, and are less easy to take benefit from when using past information.

A closer inspection however will reveal that these profits are not driven by the firm specific overreaction as we thought up to now. The smaller the firm, the higher the firm specific reaction contribution is on average, and thus the highest the contrarian profit should be if it was driven by only by the firm specific overreaction, but here it is actually smaller. At the same time the smaller the firm, the highest the unexplained profit is, which is what actually drives results. We see for example that firm specific reaction contributes positively to the contrarian strategy with a value of about 473.7%[101], 94.19%, 28.15%, 10.56% and 54.12% of total profits for the smallest to the largest sub-sample respectively, as we would expect. However at the same time in absolute terms 312.6%, 73.96%, 54.62%, 77.14% and 53.5% of profits are not explained for the smallest to the largest sample respectively, that is why although the smaller the firm the larger the firm specific overreaction contribution, but at the same time the smaller the profit. In other words, profits are not only driven by the factors in the model. Consequently our findings are consistent with theory, it is as we showed in the chapter that the model we are using that does not capture all accountable profits determinants.

Table 5.14
Decomposition of contrarian profits with time-varying factor sensitivities (single-factor model)

	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\gamma \times 10^3$	$\alpha_1\sigma_M^2 \times 10^3$	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}) \times 10^3$
Smallest Stocks	-0.13912	-26.53081	25.0302	-0.052572	0.155236
	(-0.912)	(-1.020)	(1.481)	[1.6043]	[-4.7371]
Small Stocks	-0.18968	105.1229	39.66019	0.208304	0.245971
	(-0.969)	(3.154)*	(1.83)**	[0.7977]	[0.9419]
Medium Stocks	0.16043	25.15955	13.12696	0.049854	0.081413
	(0.977)	(0.899)	(0.722)	[0.1723]	[0.2815]
Large Stocks	0.34148	27.70413	7.594781	0.054891	0.047103
	(2.044)*	(0.973)	(0.410)	[0.1230]	[0.1056]
Largest Stocks	0.48454	-34.83005	79.06886	-0.069017	0.490382
	(1.056)	(-0.445)	(1.556)	[-0.0762]	[0.5412]
All Stocks	-0.08447	-4.91200	56.12544	-0.009733	0.348088
	(-0.867)	(-0.306)	(5.211)*	[-0.0370]	[1.3388]

Notes to Table 5.14:

The coefficients α_0, α_1, and γ are obtained from the following decomposition of contrarian profits, π_t: $\pi_t = \alpha_0 + \alpha_1 (r_{M,t-1} - \bar{r}_M)^2 + \gamma\theta_{t-1} + u_t$, where $\theta_t = \frac{1}{N}\sum_{i=1}^{N} e_{i,t}^2$, $\bar{r}_M$ is the average common factor return, and $e_{i,t}$ are the residuals estimated from a version of equation (5.1).The estimate of the contrarian profits due to delayed reactions to the common factor is given by the product of α_1 and the variance of the common factor ($\alpha_1\sigma_M^2$), while an estimate of contrarian profits due to overreaction is given by: $\gamma(\frac{1}{T}\sum_{t=1}^{T}.\theta_{t-1})$. Numbers in bracket are ratios of each component relative to the average contrarian profit from Table1. Profit contributions do not add up to a 100% due to estimation errors. t-statistics appear in parentheses. * denotes significance at the 5%; ** denotes significance at the 10%

[101] There is a minus sign for the smallest sub-sample, that means that firm specific overreaction contributes negatively towards contrarian loses (π:-0.03277), and thus positively towards contrarian profits, so the contribution to "positive" profits is actually positive.

To summarize, not all profits are explained by the model, because although the contribution of the firm specific reaction is larger for smaller firms the profits move in the opposite direction. Results are of course be a manifestation of the miss measurement of risk, related to the inability of our one-factor model to explain asset returns properly, as we see when comparing them with the three factor model.

5.6.2.2 Decomposition of profits for frequently trading firms

We used here only stocks that trade continuously. If a stock does not trade for more than four consecutive weeks, it is removed for the sample for that year, but reconsidered for the other years.

For the full sample, we remove any stock that has zero returns for a period longer than two months. We also remove stocks that tend to trade once between months. The result is 146 firms in total.

However, for the sub-samples we live all 173 initial firms in, balance the portfolios, and then delete firms that we don't need. This gives us 50, 55, 90, 115, 125, 130, 140, 150, 150, 160 and 158 firms in years 1990 to 2000 respectively.

We have 10, 11, 18, 23, 25, 26, 28, 30, 30 and 32 firms in each sub-sample for 1990 to 1999. For 2000 however, we have 34 firms in the smallest sub-sample and 31 in each of the remaining 4 sub-samples.

Table 5.15
Average estimates of stock return sensitivities to current and lagged market returns & decomposition of contrarian profits (146 firms single factor)

	$\bar{b}_0$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.552368	0.204921	0.01468
	(12.662)*	(6.436)*	
Small Stocks	0.610818	0.126145	-0.00126
	(15.498)*	(4.523)*	
Medium Stocks	0.671178	0.135349	-0.02378
	(18.345)*	(4.889)*	
Large Stocks	0.685097	0.07489	-0.01872
	(18.210)*	(3.321)*	
Largest Stocks	0.704306	0.058902	-0.03653
	(21.901)*	(3.412)*	
Average	**0.644753**	**0.120041**	**-0.01312**
All Stocks	0.849830	0.125815	-0.00806
	(45.456)*	(12.551)*	
	$-\hat{\delta}\sigma_M^2$ x10^3	-Ω x10^3	$-\sigma_a^2$ x10^3
Smallest Stocks	-0.029086	0.059453	-0.256893
Small Stocks	0.002497	0.199655	-0.222027
Medium Stocks	0.047117	0.474242	-0.156135
Large Stocks	0.037091	0.502871	-0.113970
Largest Stocks	0.072379	0.383977	-0.055546
All Stocks	0.01597	0.216123	-0.006757

Notes to Table 5.15: See Notes to Table 5.13

Table 5.16
Decomposition of contrarian profits with time-varying factor sensitivities (146 firms single-factor model)

	α_0 x 10^3	α_1 x 10^3	γ x 10^3	$\alpha_1\sigma_M^2$ x 10^3	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10^3
Smallest Stocks	-0.01058	27.965	45.22312	0.055409	0.254906
	(-0.052)	(0.842)	(1.685)**	[0.1695399]	[0.7799586]
Small Stocks	0.23023	12.41572	0.09031	0.024600	0.000509
	(1.618)	(0.535)	(0.005)	[0.095171]	[0.0019691]
Medium Stocks	-0.0196	61.89045	53.951	0.122627	0.304104
	(-0.097)	(1.866)**	(2.012)*	[0.2963088]	[0.7348193]
Large Stocks	0.28757	-7.77389	37.64908	-0.015403	0.212214
	(1.722)**	(-0.285)	(1.707)**	[-0.031765]	[0.437644]
Largest Stocks	0.11819	54.20937	59.4328	0.107408	0.335001
	(0.486)	(1.365)	(1.851)**	[0.192063]	[0.5990374]
All Stocks	0.13060	9.82269	36.70131	0.019462	0.206872
	(1.391)	(0.637)	(2.935)*	[0.053880]	[0.5727213]

Notes to Table 5.16: See Notes to Table 5.14

5.6.2.3 Decomposition of profits using AR(1) OLS adjusted returns

Table 5.17
Average estimates of stock return sensitivities to current and lagged market returns & decomposition of contrarian profits (146 firms Thin trading adjustment by AR(1) OLS single-factor)

	$\bar{b}_0$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.7232 (19.745)	0.156032 (6.391)	0.021055
Small Stocks	0.699091 (19.921)	0.10193 (4.384)	0.003114
Medium Stocks	0.819729 (23.781)	0.060925 (2.981)	-0.009763
Large Stocks	0.840283 (28.996)	0.050538 (2.680)	-0.013380
Largest Stocks	0.861546 (30.268)	0.02288 (1.397)	-0.018137
Average	**0.7887698**	**0.078461**	**-0.003422**
All Stocks	0.862893 (41.9)	0.116099 (12.037)	-0.012504
	$-\hat{\delta}\sigma_M^2$ **x10³**	**-Ω x10³**	$-\sigma_a^2$ **x10³**
Smallest Stocks	-0.041718	0.484084	-0.185857
Small Stocks	-0.006169	0.420903	-0.205324
Medium Stocks	0.019343	0.498766	-0.156889
Large Stocks	0.026511	0.458633	-0.107690
Largest Stocks	0.035936	0.302339	-0.066934
All Stocks	0.024775	0.294561	-0.001833

Notes to Table 5.17: See Notes to Table 5.13

Table 5.18
Decomposition of contrarian profits with time-varying factor sensitivities (146 firms Thin trading adjustment by AR(1) OLS single-factor)

	α_0 x 10³	α_1 x 10³	γ x 10³	$\alpha_1\sigma_M^2$ x 10³	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10³
Smallest Stocks	0.454364 (2.488)*	0.162862 (0.719)	18.84736 (0.769)	0.0416314 [0.064587]	0.107899 [0.167397]
Small Stocks	0.444371 (2.135)*	31.218768 (0.937)	-8.458013 (-0.303)	0.0618556 [0.136196]	-0.0484211 [-0.106615]
Medium Stocks	0.239852 (1.558)	-1.601282 (-0.065)	18.7272 (0.907)	-0.0031727 [-0.009320]	0.1072111 [0.314941]
Large Stocks	0.065222 (0.591)	-42.745926 (-2.422)*	75.064043 (5.071)*	-0.0846951 [-0.208260]	0.4297331 [1.056688]
Largest Stocks	0.1628612 (1.283)	35.042946 (1.726)**	19.889068 (1.168)	0.06943269 [0.203215]	0.1138627 [0.333252]
All Stocks	0.136919 (1.708)**	28.797942 (2.180)*	35.207984 (3.371)*	0.05705909 [0.144016]	0.2015617 [0.508737]

Notes to Table 5.18: See Notes to Table 5.14

5.6.2.4 Decomposition of profits using AR(1) Recursive OLS adjusted returns

Table 5.19
Average estimates of stock return sensitivities to current and lagged market returns & decomposition of contrarian profits (146 firms Thin trading adjustment by Recursive AR(1) single factor)

	$\bar{b}_0$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.708983	0.161638	0.031413
	(19.533)	(6.831)	
Small Stocks	0.679417	0.104059	0.022169
	(19.349)	(4.606)	
Medium Stocks	0.816475	0.0507400	-0.011608
	(22.915)	(2.445)	
Large Stocks	0.82859	0.048041	-0.023057
	(26.639)	(2.428)	
Largest Stocks	0.867431	-0.012572	-0.027814
	(27.716)	(-0.689)	
Average	**0.780179**	**0.070381**	**-0.001779**
All Stocks	0.863164	0.116021	-0.01578
	(40.300)	(10.863)	
	$-\hat{\delta}\sigma_M^2$ **x10³**	**-Ω x10³**	$-\sigma_a^2$ **x10³**
Smallest Stocks	-0.062240	0.325462	-0.246971
Small Stocks	-0.043925	0.347673	-0.267700
Medium Stocks	0.022999	0.515758	-0.192167
Large Stocks	0.045684	0.535375	-0.146572
Largest Stocks	0.055109	0.405201	-0.110465
All Stocks	0.031266	0.289027	-0.014785

Notes to Table 5.19: See Notes to Table 5.13.

Table 5.20
Decomposition of contrarian profits with time-varying factor sensitivities (146 firms with one factor)

	α_0 x 10³	α_1 x 10³	γ x 10³	$\alpha_1\sigma_M^2$ x 10³	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10³
Smallest Stocks	0.208646	-6.400929	28.393442	-0.0126825	0.1587638
	(1.433)	(-0.259)	(1.408)	[-0.035627]	[0.445987]
	0.2196245	29.456614	1.478653	0.0583642	0.008268
Small Stocks	(1.549)	(1.224)	(0.075)	[0.201153]	[0.028496]
	0.1739435	12.931758	25.261616	0.0256225	0.141252
Medium Stocks	(1.567)	(0.686)	(1.643)	[0.071526]	[0.394308]
	0.079034	-41.323452	90.236275	-0.0818766	0.504562
Large Stocks	(0.718)	(-2.212)*	(5.918)*	[-0.163314]	[1.006421]
	0.1673709	14.846969	29.511833	0.0294172	0.1650173
Largest Stocks	(1.727)**	(0.902)	(2.199)*	[0.081515]	[0.457262]
	0.0666597	32.705241	41.394660	0.0648008	0.2314609
All Stocks	(0.966)	(2.711)*	(4.509)*	[0.179335]	[0.6405623]

Notes to Table 5.20: See Notes to Table 5.14

5.6.2.5 Decomposition of profits using an Equally weighted index

The common factor in equation (5.21) is the ASE General Price Index, a value-weighted market index. An important question that arises at this stage is whether the results are sensitive to the choice of common factor. For example, would the findings change had we employed and equally-weighted index of all stocks in the sample, rather than the value-weighted[102] ASE GPI? Would the performance of the single-factor model improve? In order to investigate this possibility, we test using an equally weighted index of all stocks in the sample.

Results are presented in Tables 5.21 and Table 5.22. We can see that now, on average, equity returns in the ASE react stronger to the contemporaneous common factor and weaker to the lagged factor (Table 5.21). For example, the average slope coefficient on the lagged factor is now 0.090787 (from 0.57997 in Table 5.13 where we have the value weighted index) and this effect is more pronounced for small firms, as we would expect. The average slope coefficient on the contemporaneous factor is 0.792519 (from 0.252241 in Table 5.13). We could say here that the largest and especially the large stocks that react almost instantaneously, lead the smallest stocks that have the highest lagged slope coefficient (0.17789). We would expect such a relationship, as larger firms adjust to information faster than smaller ones do. This relationship can contribute positively to contrarian profits, consistent with the findings in table 5.13. The part of contrarian profits due to common factor reactions is still relatively small for the full sample. (0.00803 from 0.003744 in Table 5.13). The

[102] See Appendix (5.6.4) figures 5.25 to 5.27 and figures 5.51 to 5.53.

term $-\Omega$, is larger for the full sample (from 0.143985 it grows to 0.227144) and it still grows smaller as we move from the largest stock sub-sample to the smallest stock sub-sample. Note also that the unexplained contrarian profits ($-\sigma_a^2$) are now smaller for most sub-samples.

Table 5.21
Average estimates of stock return sensitivities to current and lagged market returns & decomposition of contrarian profits (single-factor and an equally weighted index)

	$\bar{b}_o$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.626989 (17.306)*	0.17789 (5.771)*	-0.03246
Small Stocks	0.786644 (21.950)*	0.151827 (4.309)*	-0.13273
Medium Stocks	0.845417 (23.845)*	0.097622 (3.232)*	-0.11746
Large Stocks	0.909612 (25.168)*	0.027603 (0.989)	-0.12284
Largest Stocks	0.793932 (21.903)	-0.001004 (-0.054)	-0.09773
Average	**0.792519**	**0.090787**	**-0.10065**
All Stocks	1.00426 (40.329)*	-0.00248 (-0.239)	-0.00464
	$-\hat{\delta}\sigma_M^2$ **x10**^{3}	**-Ω x10**^{3}	$-\sigma_a^2$ **x10**^{3}
Smallest Stocks	0.05620602	0.2098936	-0.11975
Small Stocks	0.22982378	0.478083	-0.09356
Medium Stocks	0.20337635	0.5018154	-0.07587
Large Stocks	0.21269959	0.4806447	-0.08417
Largest Stocks	0.16921829	0.6287556	-0.05164
All Stocks	0.00802904	0.2271445	-0.00781

Notes to Table 5.21:

See Notes to table 5.13

The results from the decomposition of contrarian profits with time-varying factor sensitivities and the equally-weighted index are presented in Table 5.22, and are similar to the results in Table 5.14. For example, the constant coefficient estimates are statistically insignificant with the exception of the estimates in the large stock sub-sample (*t*-statistic: 2.157), while the slope coefficient estimates (α_1) are all statistically insignificant (were significant only for the small stocks sub-sample in Table 5.14). The estimates of γ are now statistically significant at the 5% level for the whole sample and all sub-samples except for the large one. The contrarian profits proportion attributed to firm-specific overreaction for all-stocks are now slightly larger 145.4% (from 133.8% in Table 5.14). The contribution of common factor underreaction to the profits is now positive but still very low (3.7%). There is therefore still a large portion of profits not accounted for (about -36.7% compared to the -30.0% when using the ASE index as a proxy for the common factor). With respect to the sub-samples we witness that firm specific reactions contribute positively to the contrarian strategy with a value of about 701.6%[103], 177.1%, 81.0%, 16.5% and 75.2% of total profits for the smallest to the largest sub-sample respectively, as we would expect. However profits do not increase in the manner they should having described the contributions of the significant factors above. This is because in absolute terms a proportion of profits are still not explained: 515.4%, 75.57%, 35.56%, 83.16% and 34.98% for the smallest to the largest sample respectively. The missing facet not explained by the model ads to most stocks' profits as they get larger apart for the largest sub-sample[104].

To summarise the findings in this section, when an equally-weighted index of all stocks is employed equity returns in the ASE (on average) react stronger to

[103] As before, there is a minus sign for the smallest sub-sample, that means that firm specific overreaction contributes negatively towards contrarian loses and positively towards profits.

the contemporaneous common factor and weaker to the lagged factor, with larger firms acting almost instantaneously, and acting as lead firms. The rest of the results are very similar to the ones with the value-weighted index.

Table 5.22
Decomposition of contrarian profits with time-varying factor sensitivities (single-factor and an equally-weighted index)

	α_0 x 10^3	α_1 x 10^3	γ x 10^3	$\alpha_1\sigma_M^2$ x 10^3	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10^3
Smallest Stocks	-0.236062	-16.31272	41.57489	-0.02824	0.2299056
	(-1.525)	(-0.682)	(2.101)*	[0.8618]	[-7.0157]
Small Stocks	-0.199897	-2.29240	83.62828	-0.00397	0.4624573
	(-0.1)	(-0.074)	(3.273)*	[-0.0152]	[1.7709]
Medium Stocks	0.104134	-27.70465	42.37972	-0.04797	0.2343562
	(0.626)	(-1.078)	(1.993)*	[-0.1658]	[0.8102]
Large Stocks	0.366677	0.916392	13.30024	0.001587	0.0735492
	(2.157)*	(0.035)	(0.612)	[0.0036]	[0.1649]
Largest Stocks	0.320132	-56.35943	124.1731	-0.09758	0.6866668
	(0.688)	(-0.784)	(2.088)*	[-0.1077]	[0.7578]
All Stocks	-0.129078	5.517889	67.74899	0.009554	0.3746461
	(-1.310)	(0.362)	(5.378)*	[0.037079]	[1.4540128]

Notes to Table 5.22:

See Notes to table 5.14

We thus conclude that the overall analysis does not improve, and the unexplained contribution increases as well. Because using the ASE GPI as our market proxy provides estimates that are more modest, we perform all other tests using it as the common factor. We have an additional motive -now that this explanation has failed-, to look in to the January effect as another possible explanation that might improve on the single-factor model's performance.

[104] For example the unaccounted factors' contribution is -515.4%, -75.57%, 35.56%, 83.16% and 34.98%. So for the smallest stocks its very negative, for the small stocks its less negative, and then it gets positive and increasing up to the large sub-sample.

5.6.2.6 Decomposition of profits under seasonality

In view of the findings mentioned in the literature review, an important question is whether the above results are due to the well-known January-effect (Rozeff and Kinney, 1976). In order to investigate this possibility, we re-examine the contribution of our factors to contrarian profits for the all-sample group and the five size-sorted sub-samples, *without* the first four weeks of the year, that is, for February to December (DeBondt and Thaler 1985,1987, Conrad and Kaul 1993). If there is any specific problem associated with January, then it should vanish when we exclude it. For example if the disability of our model to explain a large portion of the predictability is related to January, then this will disappear when we exclude it. On the other hand, if the strand in the literature that supports the idea that overreaction and lead-lag structure effects occur only in the month of January[105], then even the proportion of profits explained earlier by our model, should decrease significantly.

Results from re-estimating equation (5.21) are presented in Table 5.23. When January returns are excluded, weekly equity returns in the ASE, on average, seem to have a stronger contemporaneous reaction to the common factor compared to the full sample. For example, the average slope coefficient on the contemporaneous factor is 0.600635 (from 0.252241 when January is included in Table 5.13), while the average slope coefficient on the lagged factor is -0.11313 (from 0.57997 when January is included). For all size-sorted sub-samples, the slope coefficient on the contemporaneous factor is now much higher than before, and the reaction to the contemporaneous common factor increases monotonically with size, consistent with the fact that larger, more followed firms, discount news earlier. In addition, the slope coefficient on the lagged factor is now much lower and negative, which suggests that common factor underreaction documented in Table 5.13 is confined in January[106]. Looking at $\hat{\delta}$ we expect a possible positive common factor contribution to contrarian profits, and that this contribution is due overreaction. The reactions to the common factor contribute more to the contrarian profits of large firms and less to the contrarian profits of medium to small firms when January returns are excluded.

The negative of the average autocovariance of the error term, is still quite large for the full sample, and it still grows smaller as we move from the largest stock sub-sample (0.790513) to the smallest stock sub-sample (0.123658). This indicates that overreaction to firm-specific information still contributes more to the contrarian profits of large firms, and less to the contrarian profits of small firms, irrespective of any seasonal effects. The effect of $(-\sigma_a^2)$ is very similar as before when we included the month of January. Taken together, results here, suggest contrarian profits even out of January. The explained portion of these profits is more due to firm specific overreaction rather than reaction to the common factor, when January returns are excluded.

[105] Or in January and only for small firms, or January for extreme size portfolios (based on the notion that fund-managers sell large less risky firms on January, to long small risky firms, once their original blue chip portfolio has been accepted by the board, in order to boost up returns.
[106] This could also be owed to the index been comprised of the largest and more heavily traded firms. It is logical then, that they would seem to lead the market by overreacting to the lagged value of the market, since it might be that the market follows their moves which determine the ASE GPI movements, also agents might invest based on movements of these large stocks, and determine the market index level.

Table 5.23
Average estimates of stock return sensitivities to current and lagged market returns & decomposition of contrarian profits
(single-factor Feb-Dec)

	$\bar{b}_o$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.419757	-0.04015	-0.07856
	(10.544)*	(-1.222)	
Small Stocks	0.570737	-0.05725	-8.78E-02
	(12.551)*	(-2.091)*	
Medium Stocks	0.640478	-0.05725	1.69E-02
	(14.594)*	(-2.091)*	
Large Stocks	0.669506	-0.17315	-1.66E-01
	(14.946)*	(-5.215)*	
Largest Stocks	0.710011	-0.23921	-1.48E-01
	(18.371)*	(-11.275)*	
Average	**0.600635**	**-0.11313**	**-0.09903**
All Stocks	0.77404	0.11479	-0.00459
	(34.147)*	(13.316)*	
	$-\hat{\delta}\sigma_M^2$ **x10**^{3}	**-Ω x10**^{3}	$-\sigma_a^2$ **x10**^{3}
Smallest Stocks	0.158097	0.123658	-0.27983
Small Stocks	0.176644	0.309953	-0.2941
Medium Stocks	-0.03403	0.538613	-0.23601
Large Stocks	0.334106	0.493806	-0.17294
Largest Stocks	0.298425	0.790513	-0.14552
All Stocks	0.009237	0.150036	-0.00755

Notes to Table 5.23:

See Notes to table 5.13

The results for re-estimating equation (5.18) are presented in Table 5.24 and we can see that the γ estimates are statistically significant for all but the medium and large stocks. Contrarian profits due to firm-specific overreaction for all-stocks are 141.69% (0.354233 / 0.25)[107]; also, contrarian profits due to common factor reaction for all-stocks are 0.1604% (0.000401 / 0.25). Still some portion (about 40% compared to 30% with January included) of contrarian profits is not explained.

Table 5.24
Decomposition of contrarian profits with time-varying factor sensitivities (single-factor Feb-Dec)

	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\gamma \times 10^3$	$\alpha_1\sigma_M^2 \times 10^3$	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}) \times 10^3$
Smallest Stocks	-0.275385	-21.66785	39.46819	-0.043201	0.243859
	(-1.76074)**	(-0.82492)	(2.13251)*	[0.2186]	[-1.2340]
Small Stocks	-0.20182	36.52838	64.89602	0.07283	0.400969
	(-0.96399)	(1.03892)	(2.61948)*	[0.2165]	[1.1921]
Medium Stocks	0.113977	87.96631	-0.304266	0.175386	-0.00188
	(0.65439)	(3.00730)*	(-0.01476)	[0.5883]	[-0.0063]
Large Stocks	0.434047	-6.150349	-2.898314	-0.012262	-0.017908
	(2.65926)*	(-0.22437)	(-0.15006)	[-0.0327]	[-0.0477]
Largest Stocks	0.035623	-123.1932	194.1932	-0.245621	1.203013
	(0.07247)	(-1.49235)	(3.34740)*	[23.672]	[-115.942]
All Stocks	-0.10555	0.201009	57.33193	0.000401	0.354233
	(-1.04151)	(0.11861)	(5.19505)*	[0.001604]	[1.4169]

Notes to Table 5.24:

See Notes to table 5.14,

Excluding January does not eliminate contrarian profits related to common and firm specific reactions, which still exist. The January effect, does not explain as the overreaction contributions. The problem persists, and is related to risk miss measurement of the single factor model as we have shown. The three-factor model is superior to the single-factor model. The later does not outperform the first, no matter the considerations that we take with respect to thin-trading, seasonality, the market index used etc.

[107] Excluding January, full sample profits do not change significantly. For the sub-samples, apart for the largest one, they increase significantly, more specifically, the profits are: -0.19762, 0.33635, 0.29809, 0.37485, -0.01038 for the smallest to the largest sub-sample respectively.

5.6.3 Using recursive AR(1) thin-trading adjusted returns multi-factor analysis.

Table 5.25
Average estimates of stock return sensitivities to current and lagged market returns (146 firms, AR(1)-recursive. 3 factors)

	$\bar{b}_{o,M}$	$\bar{b}_{1,M}$	$\hat{\delta}_M$
Smallest Stocks	0.992311 (24.115)*	0.017103 (0.677)	-0.099447
Small Stocks	0.909277 (20.83)*	-0.000572 (-0.022)	-0.077821
Medium Stocks	1.008072 (25.077)*	-0.028948 (-1.092078)	-0.028948
Large Stocks	1.004199 (28.203)*	-0.026828 (-1.015)	-0.08728
Largest Stocks	0.926323 (31.894)*	-0.054792 (-2.901)*	-0.056930
Average	**0.968036**	**-0.018807**	**-0.070085**
All Stocks	0.979208 (47.557)*	0.081164 (7.560)*	-0.013155
	$\bar{b}_{o,SMB}$	$\bar{b}_{1,SMB}$	$\hat{\delta}_{SMB}$
Smallest Stocks	0.412526 (8.529)*	0.342366 (6.459)*	-0.268641
Small Stocks	0.288854 (7.733)*	0.184959 (4.345)*	-0.100932
Medium Stocks	0.190513 (5.783)*	0.0880715 (2.258)*	-0.049045
Large Stocks	0.082996 (3.091)*	0.014877 (0.448)	-0.007088
Largest Stocks	-0.051144 (-2.344)*	-0.091447 (-3.264)*	-0.030905
Average	**0.184749**	**0.1077653**	**-0.0913222**
All Stocks	0.149530 (11.764)*	0.39675 (16.340)*	0.024267
	$\bar{b}_{o,HML}$	$\bar{b}_{1,HML}$	$\hat{\delta}_{HML}$
Smallest Stocks	0.063129 (1.339)	-0.027704 (-0.638)	0.085432
Small Stocks	0.051229 (1.233)	-0.057203 (-1.595)	0.011702
Medium Stocks	-0.027054 (-0.645)	-0.042791 (-1.268)	-0.005486
Large Stocks	-0.007347 (-0.221)	-0.095776 (-3.075)*	0.011681
Largest Stocks	-0.023282 (-0.770)	-0.008088 (-0.351)	-0.004350
Average	**0.011335**	**-0.0463124**	**0.0197958**
All Stocks	-0.056389 (-3.477)*	-0.041864 (-3.878)*	0.001834

Notes to Table 5.25:

See Notes to Table 5.5.

Table 5.26
Decomposition of contrarian profits
(146 firms, AR(1)-recursive. 3 factors)

	$-\hat{\delta}\sigma_M^2$ x10^3	$-\hat{\delta}\sigma_{SMB}^2$ x10^3	$-\hat{\delta}\sigma_{HML}^2$ x10^3
Smallest Stocks	0.197057	0.394562	-0.078667
Small Stocks	0.154205	0.148242	-0.010775
Medium Stocks	0.057361	0.072034	0.005052
Large Stocks	0.172948	0.010410	-0.010756
Largest Stocks	0.112808	0.045391	0.004006
All Stocks	0.026067	-0.035642	-0.001689
	-Ω x10^3	$-\sigma_a^2$ x10^3	
Smallest Stocks	0.455180	-0.143075	
Small Stocks	0.504141	-0.173289	
Medium Stocks	0.548746	-0.110467	
Large Stocks	0.507718	-0.079751	
Largest Stocks	0.292899	-0.076893	
All Stocks	0.446199	-0.012951	

Notes to Table 5.26:

See Notes to Table 5.6.

Table 5.27
Decomposition of contrarian profits with time-varying factor sensitivities
(146 firms, AR(1)-recursive. 3 factors)

	α_0 x 10^3	α_1 x 10^3	γx 10^3	$\alpha_1\sigma_M^2$ x 10^3	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10^3
	0.1497	-7.9469	42.21	-0.015747	0.220155
Smallest Stocks	(0.958)	(-0.325)	(1.738)**	[-0.0442]	[0.6184]
	0.2244	29.9252	0.4865	0.059297	0.002537
Small Stocks	(1.473)	(1:255)	(0.023)	[0.2044]	[0.0087]
	0.1484	13.4353	31.6971	0.026622	0.165323
Medium Stocks	(1.244)	(0.720)	(1.711)**	[0.0743]	[0.4615]
	-0.01365	-39.6147	113.5049	-0.078498	0.592009
Large Stocks	(-0.116)	(-2.147)*	(6.194)*	[-0.1566]	[1.1808]
	0.0789	11.3348	49.8114	-0.078497	0.259802
Largest Stocks	(0.761)	(0.699)	(3.092)*	[0.0622]	[0.7199]
	0.0301	34.0399	50.9772	0.067451	0.265883
All Stocks	(0.398)	(2.834)*	(4.378)*	[0.1867]	[0.7358]

Notes to Table 5.27:

See Notes to Table 5.7.

5.6.4 Plots of profits, returns, distributions etc

Figure 5.1
Cumulative Average Profit Plot for the all-sample group
(Created from Risk Adjusted Returns)

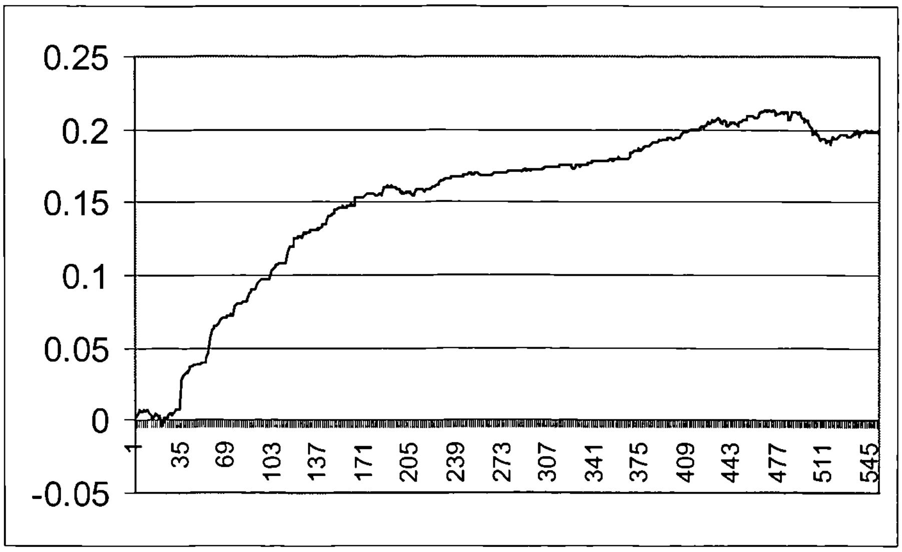


Figure 5.2
Cumulative Average Profit Plot for the smallest sub-sample
(Created from Risk Adjusted Returns)

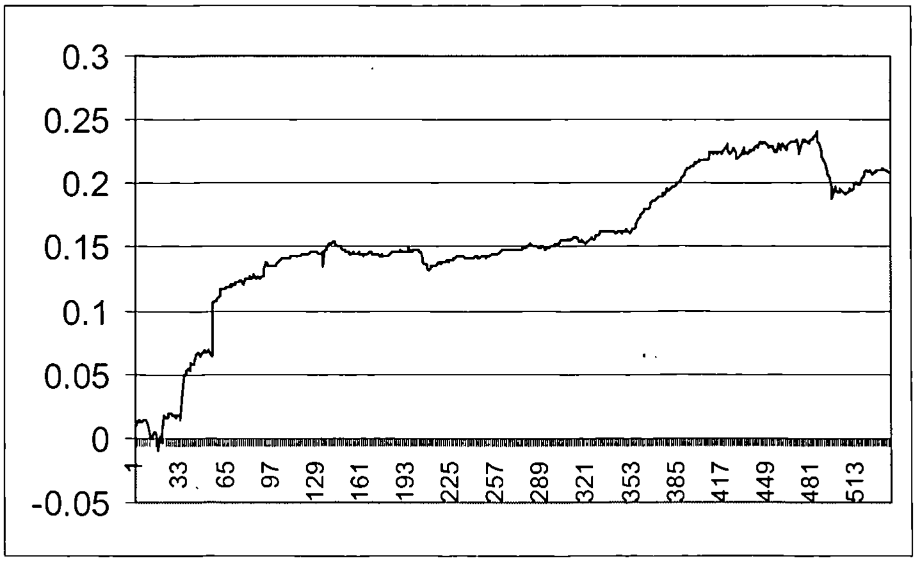


Figure 5.3
Cumulative Average Profit Plot for the small sub-sample
(Created from Risk Adjusted Returns)

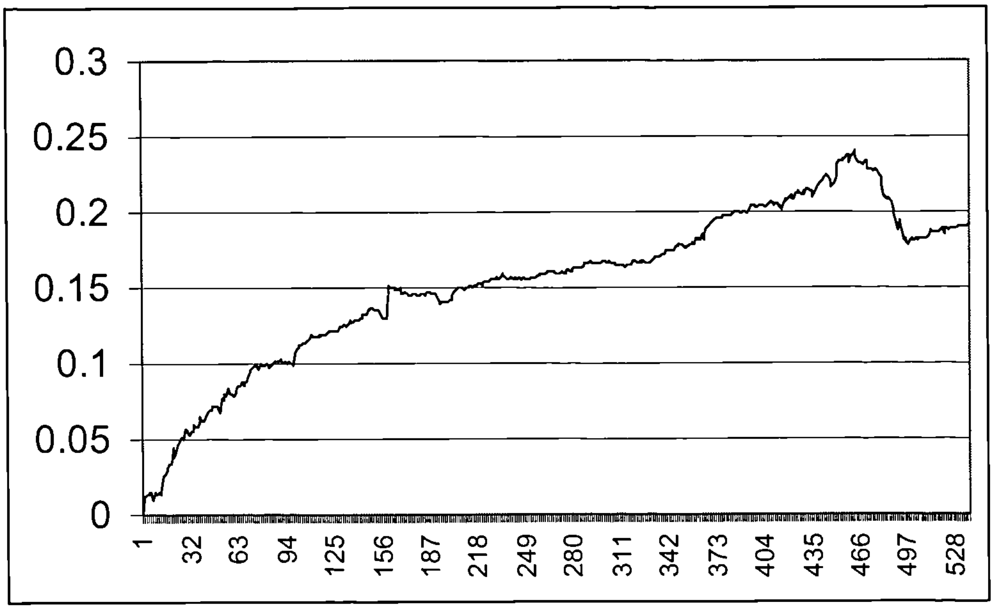


Figure 5.4
Cumulative Average Profit Plot for the medium sub-sample
(Created from Risk Adjusted Returns)

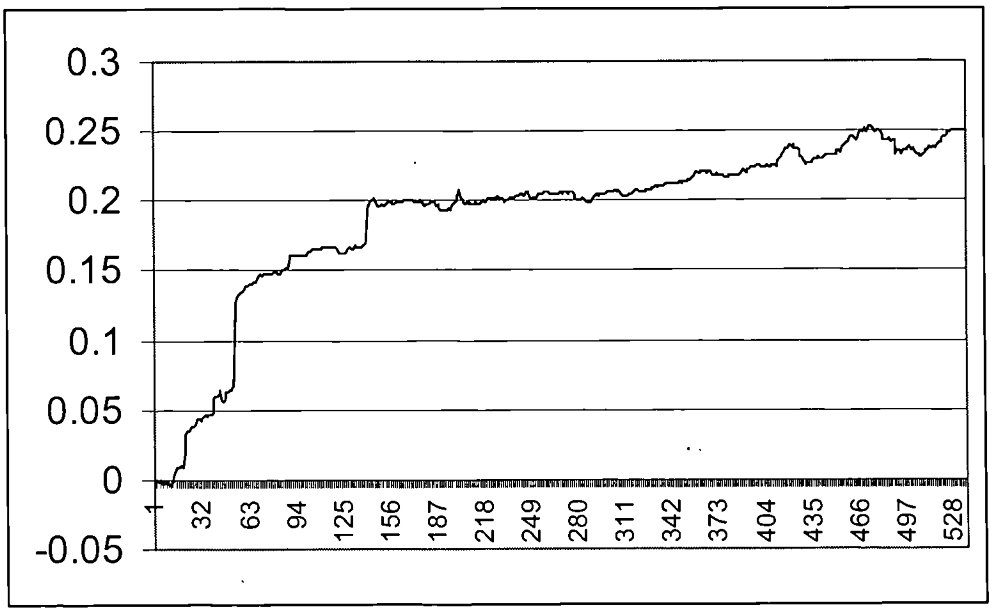


Figure 5.5
Cumulative Average Profit Plot for the large sub-sample
(Created from Risk Adjusted Returns)

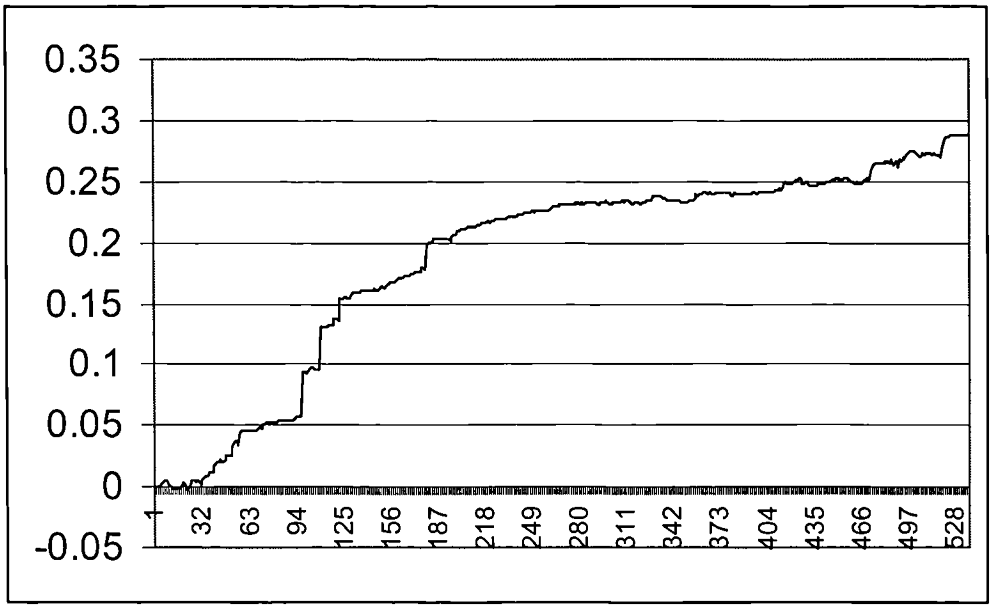


Figure 5.6
Cumulative Average Profit Plot for the largest sub-sample
(Created from Risk Adjusted Returns)

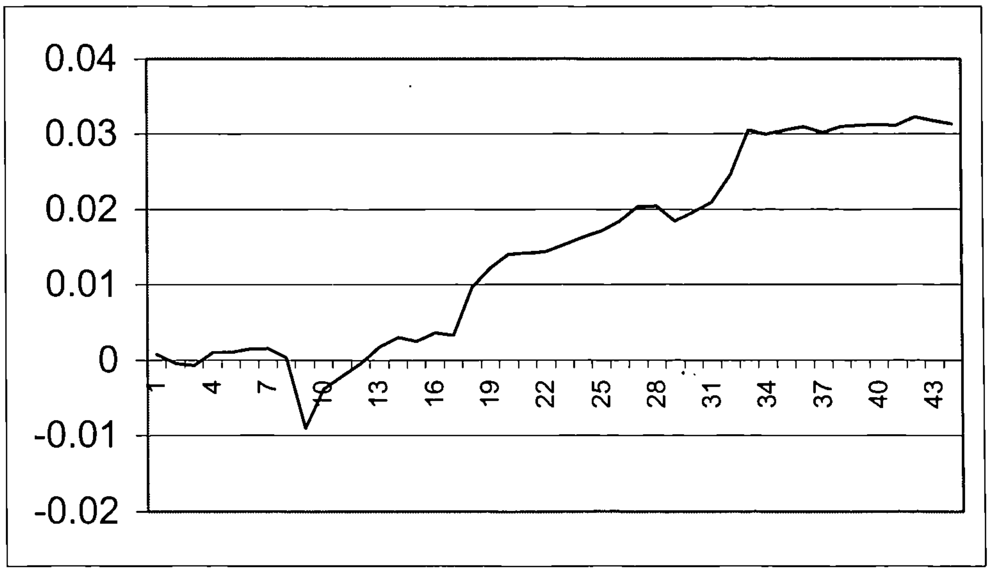


Figure 5.7
Cumulative Average Profit per Euro Long Plot for the all-sample group (Created from Risk Adjusted Returns)

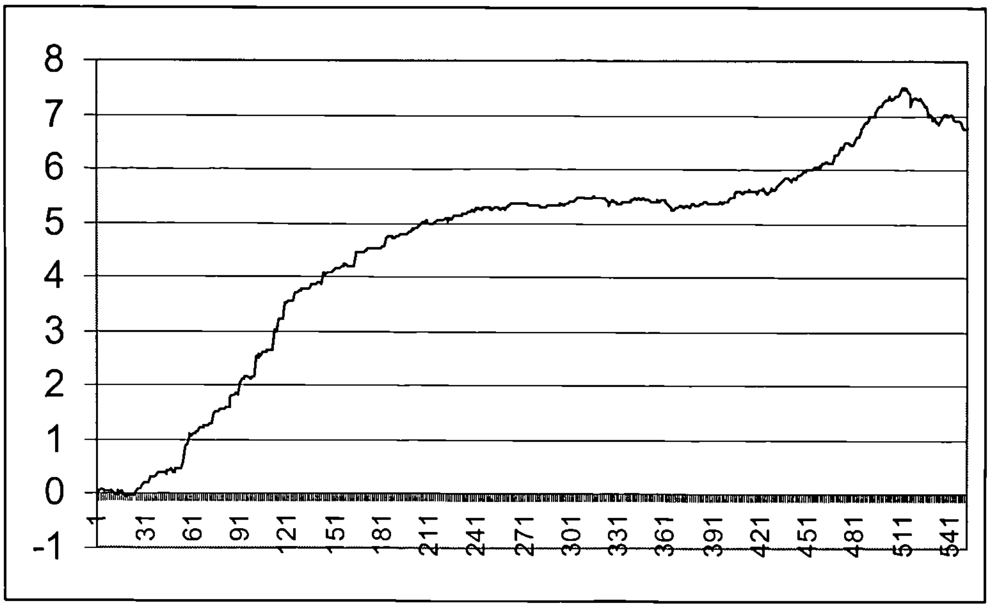


Figure 5.8
Cumulative Average Profit per Euro Long Plot for the smallest sub-sample (Created from Risk Adjusted Returns)

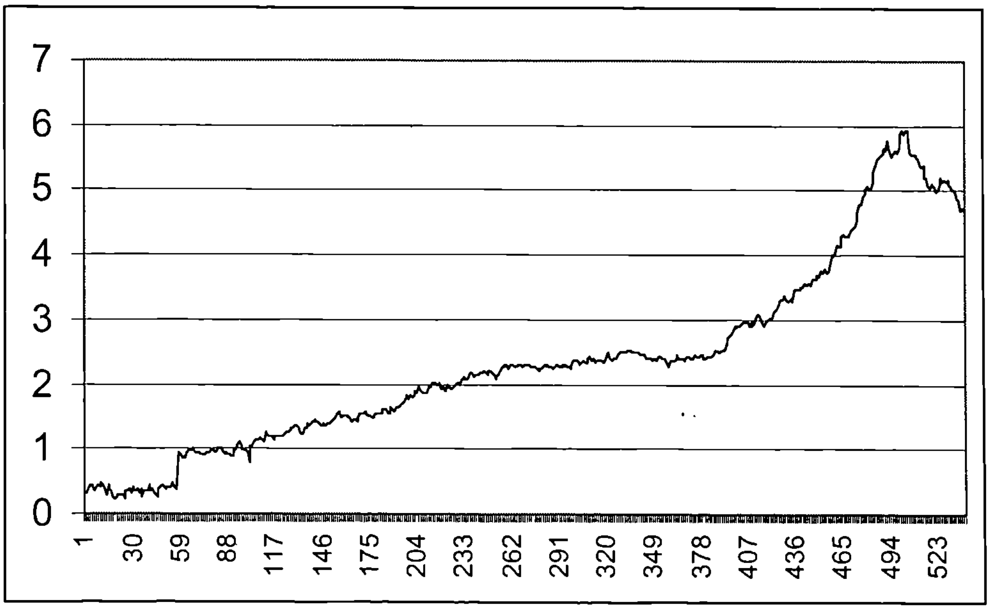


Figure 5.9
Cumulative Average Profit per Euro Long Plot for the small sub-sample (Created from Risk Adjusted Returns)

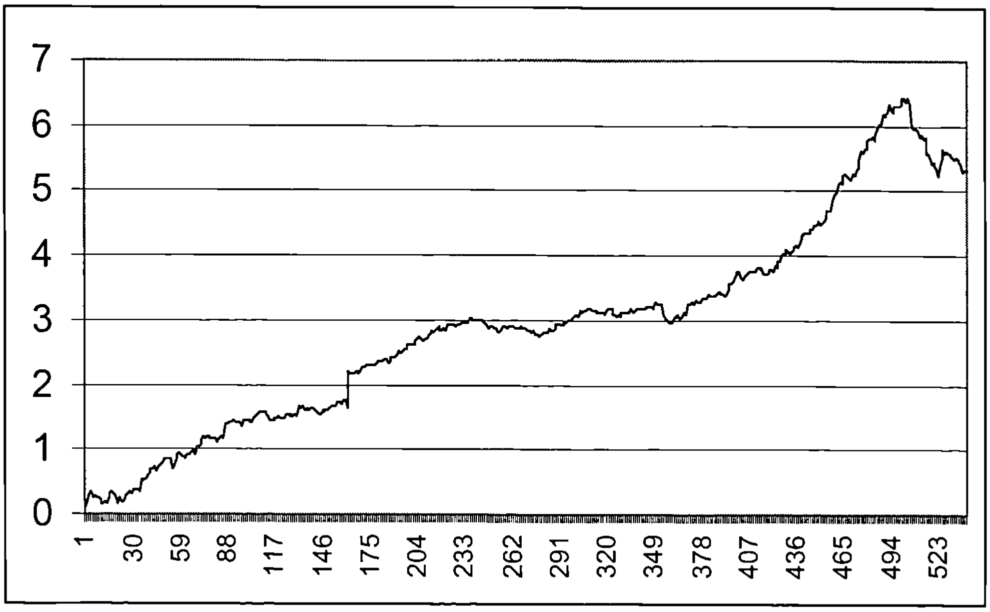


Figure 5.10
Cumulative Average Profit per Euro Long Plot for the medium sub-sample (Created from Risk Adjusted Returns)

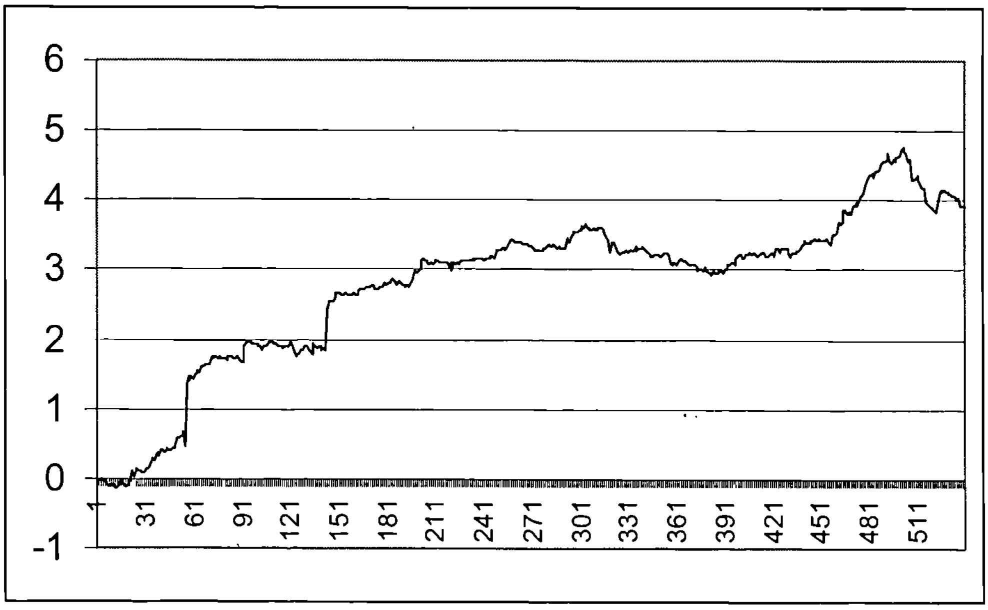


Figure 5.11
Cumulative Average Profit per Euro Long Plot for the large sub-sample (Created from Risk Adjusted Returns)

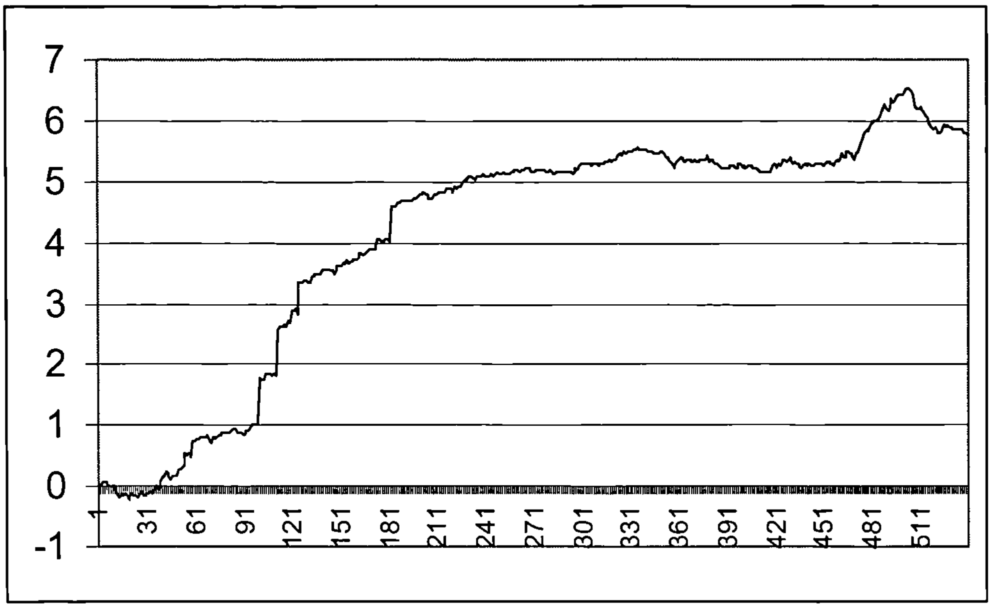


Figure 5.12
Cumulative Average Profit per Euro Long Plot for the largest sub-sample (Created from Risk Adjusted Returns)

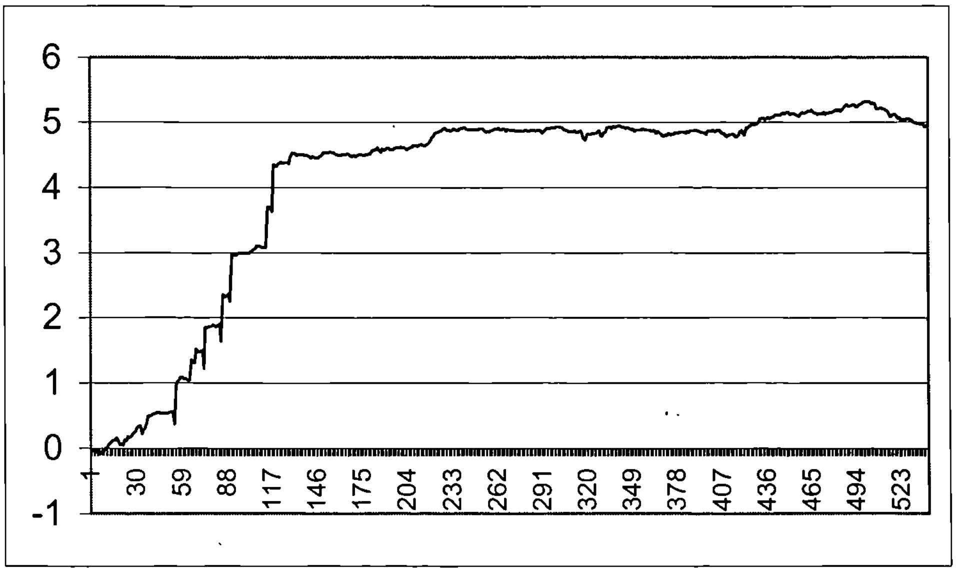


Figure 5.13
Average Returns for all firms (all sample period)

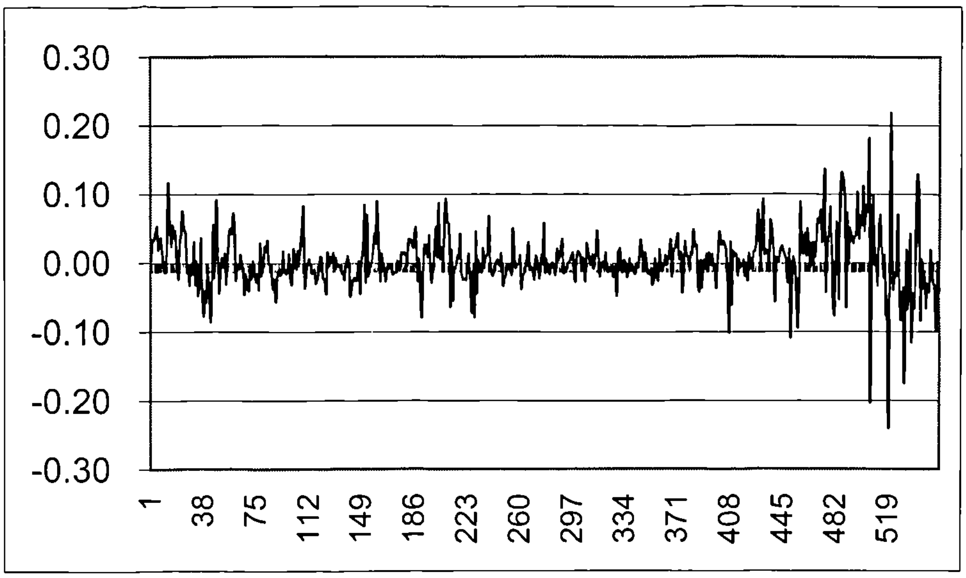


Figure 5.14
Average Returns for all firms Histogram (all sample period)

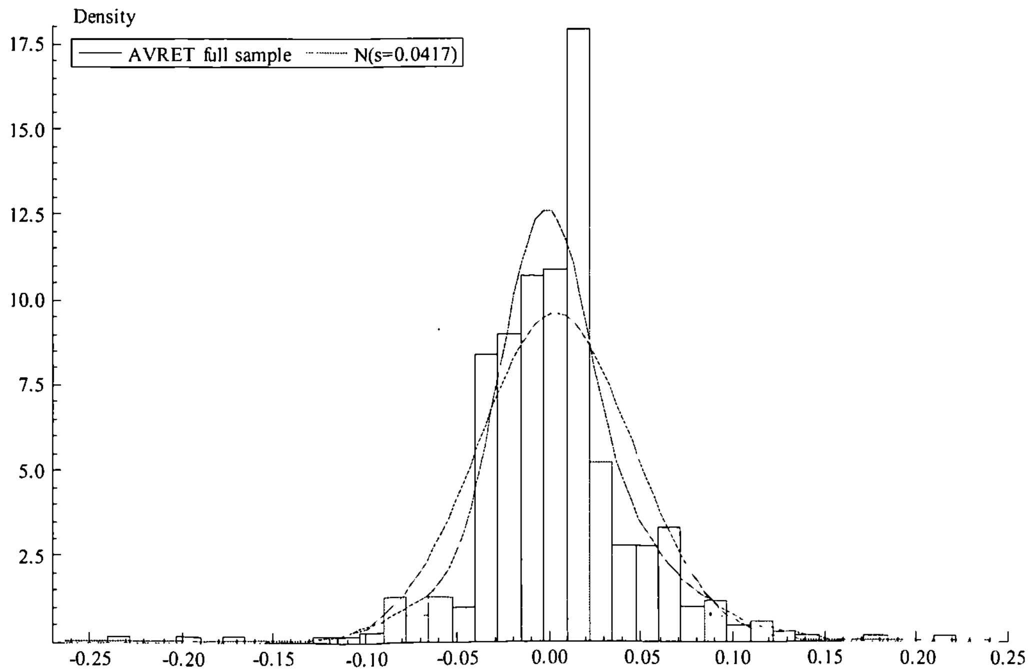


Figure 5.15
Average Returns for smallest firms (all sample period)

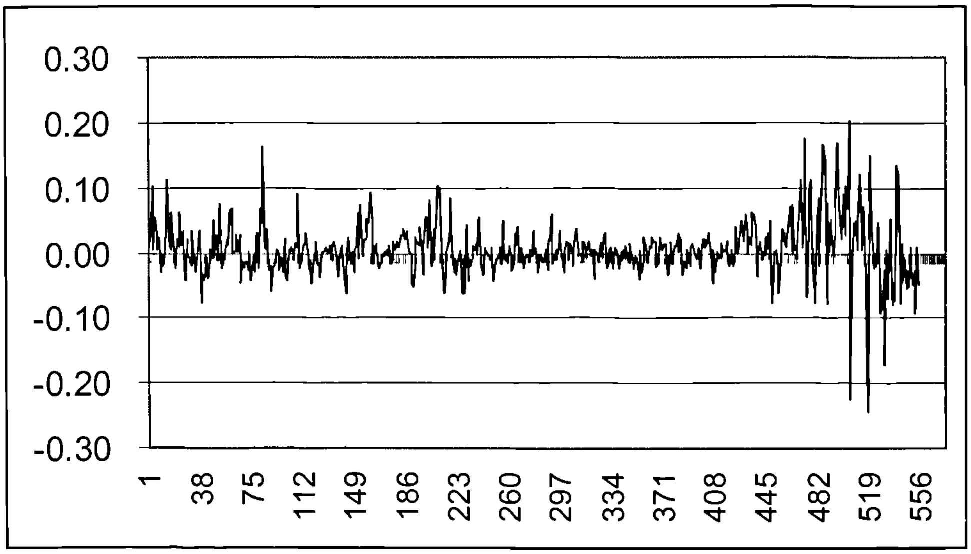


Figure 5.16
Average Returns for smallest firms Histogram (all sample period)

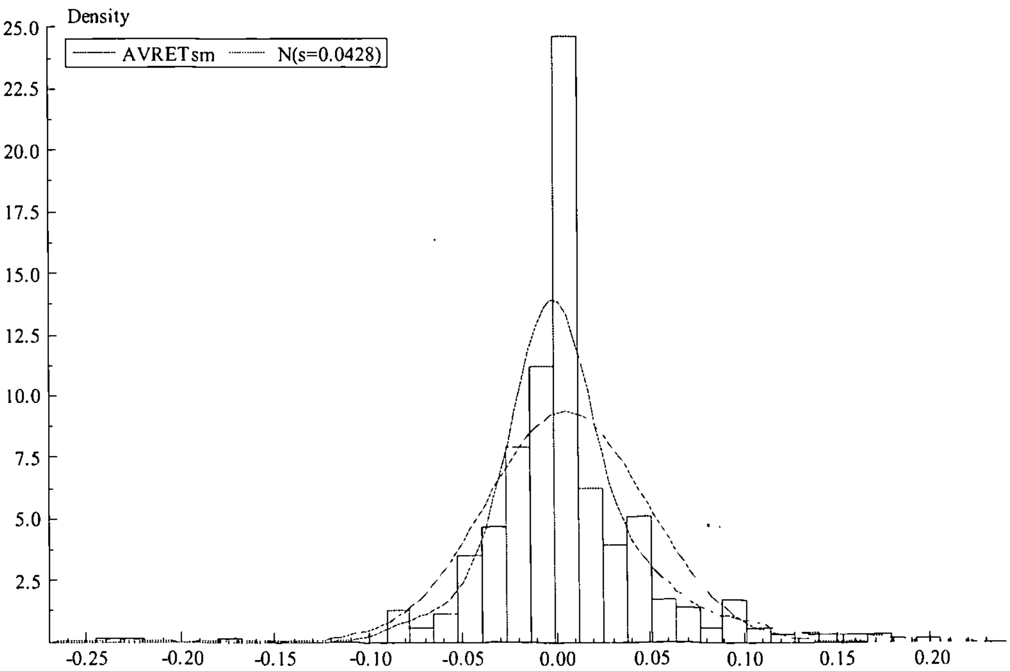


Figure 5.17
Average Returns for small firms (all sample period)

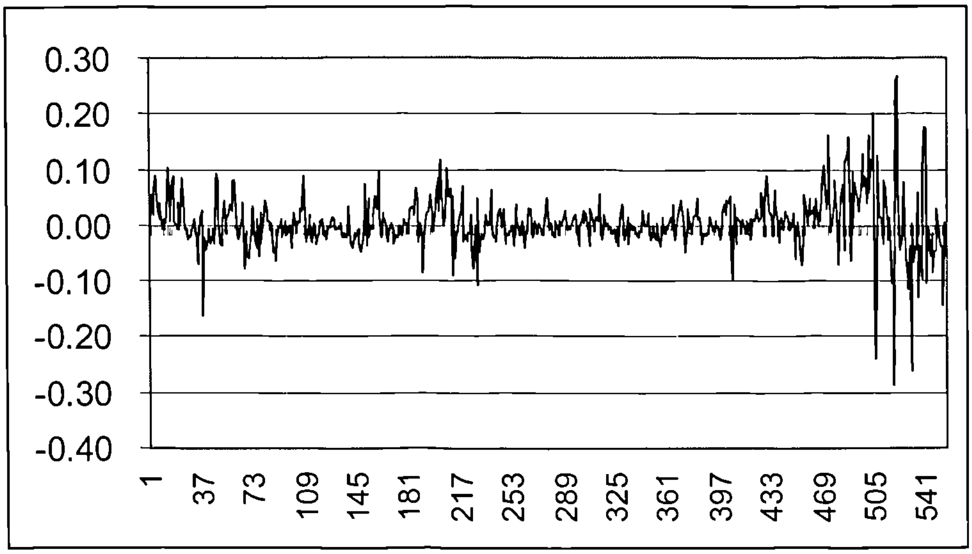


Figure 5.18
Average Returns for small firms, Histogram (all sample period)

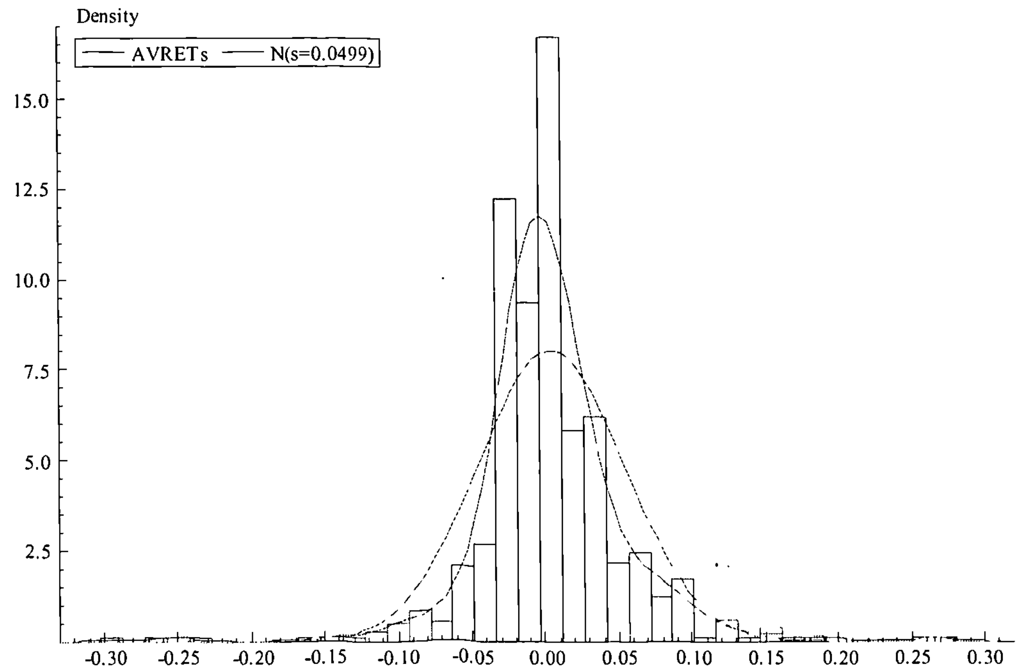


Figure 5.19
Average Returns for medium firms (all sample period)

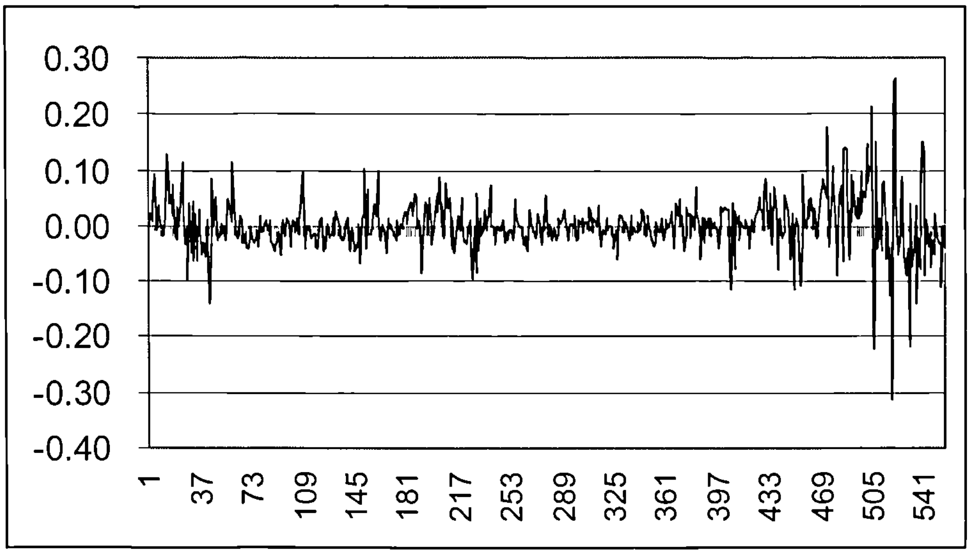


Figure 5.20
Average Returns for medium firms Histogram (all sample period)

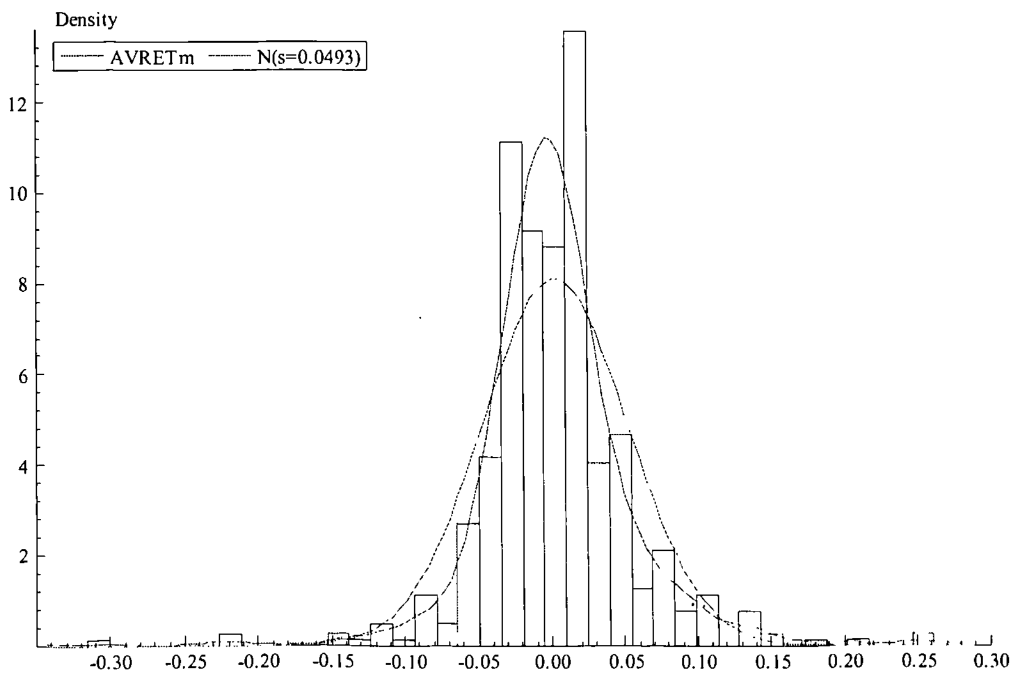


Figure 5.21
Average Returns for large firms (all sample period)

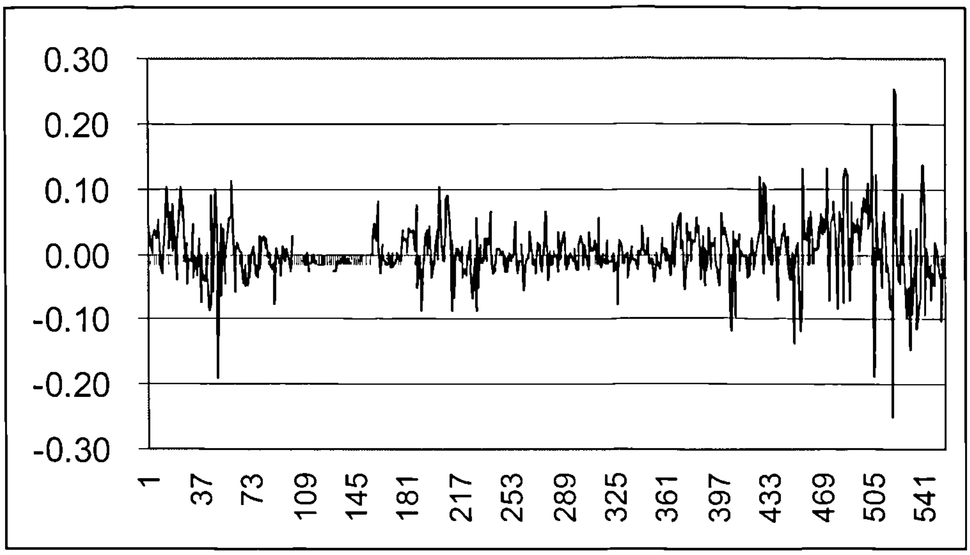


Figure 5.22
Average Returns for large firms Histogram (all sample period)

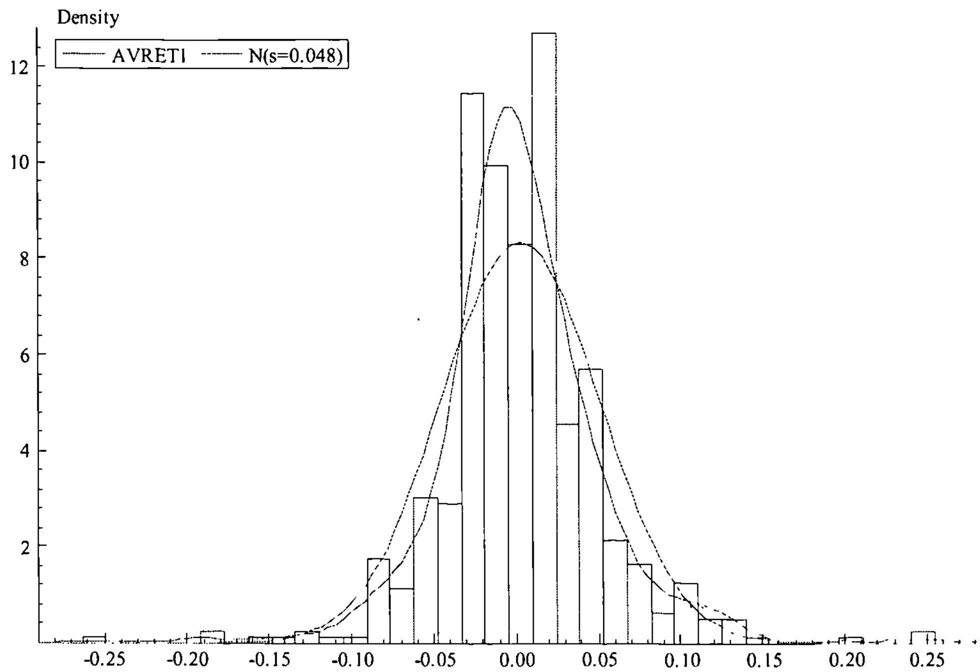


Figure 5.23
Average Returns for largest firms (all sample period)

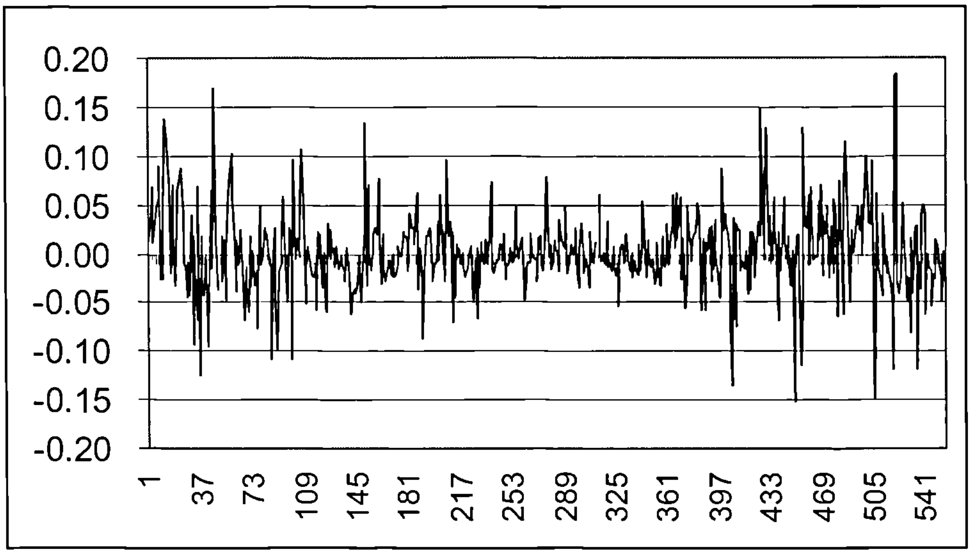


Figure 5.24
Average Returns for largest firms Histogram (all sample period)

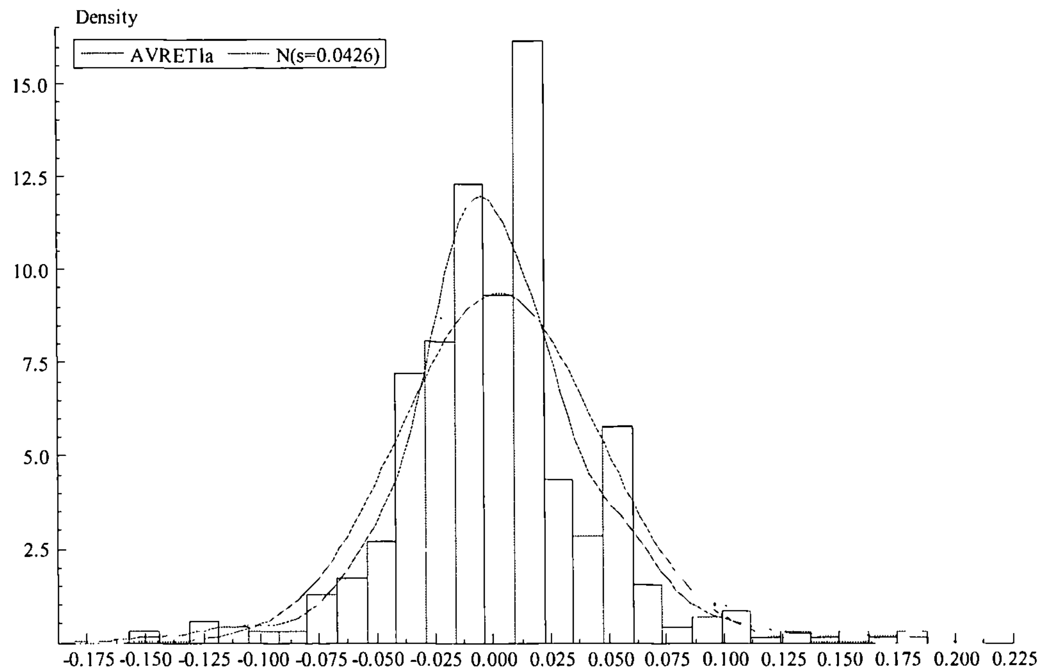


Figure 5.25
ASE GPI Returns (all sample period)

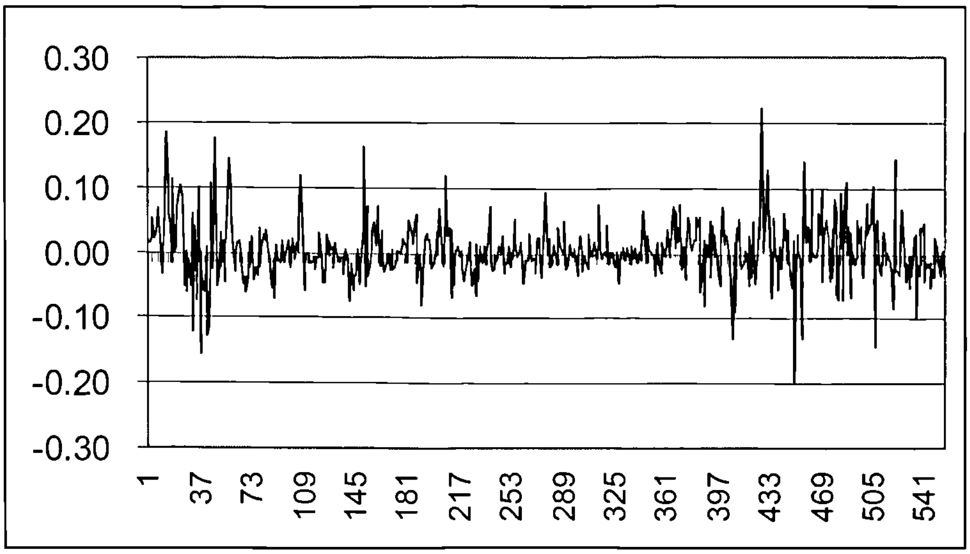


Figure 5.26
ASE GPI Returns Histogram (all sample period)

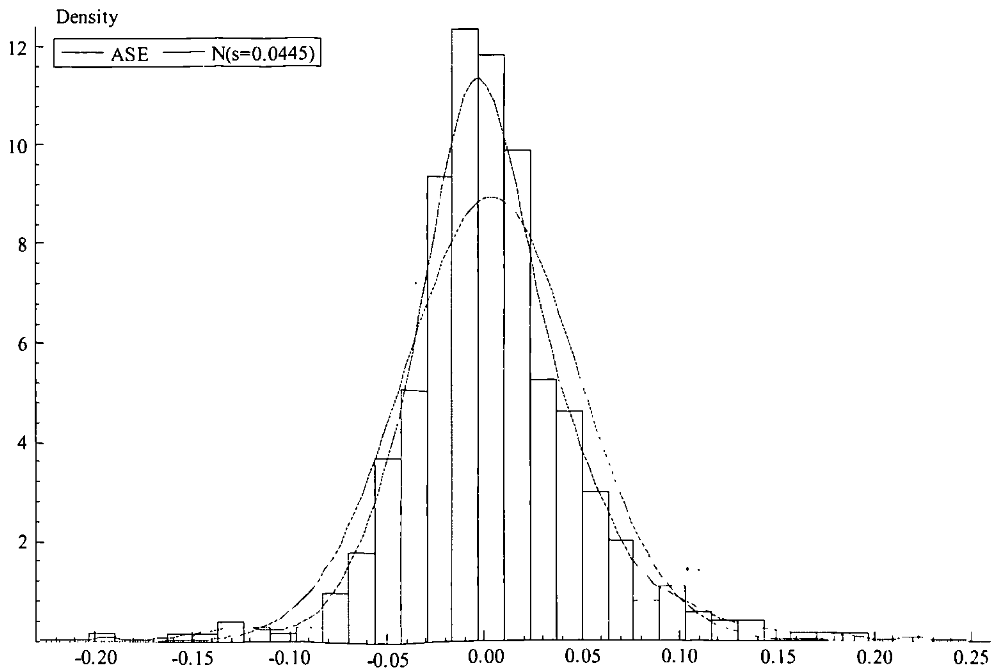


Figure 5.27
ASE GPI & Average Returns Scatter Plot (all sample period)

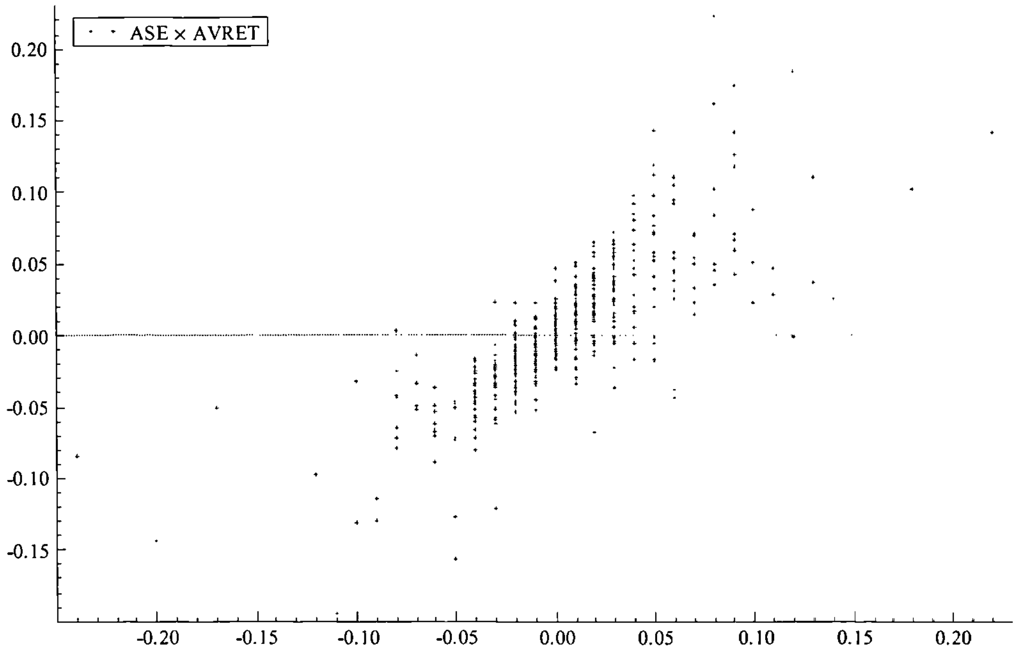


Figure 5.28
Profits For Full sample (all sample period)

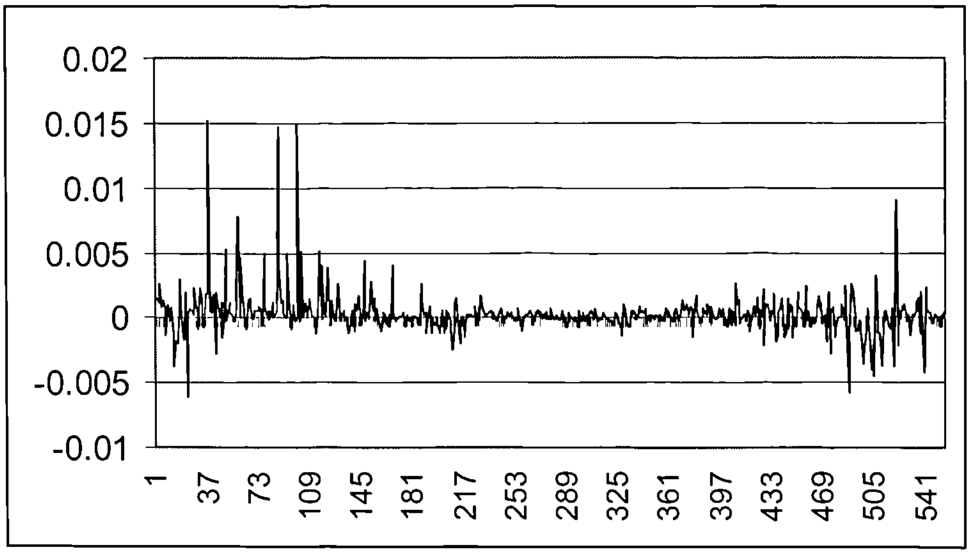


Figure 5.29
Profits For Full sample Histogram (all sample period)

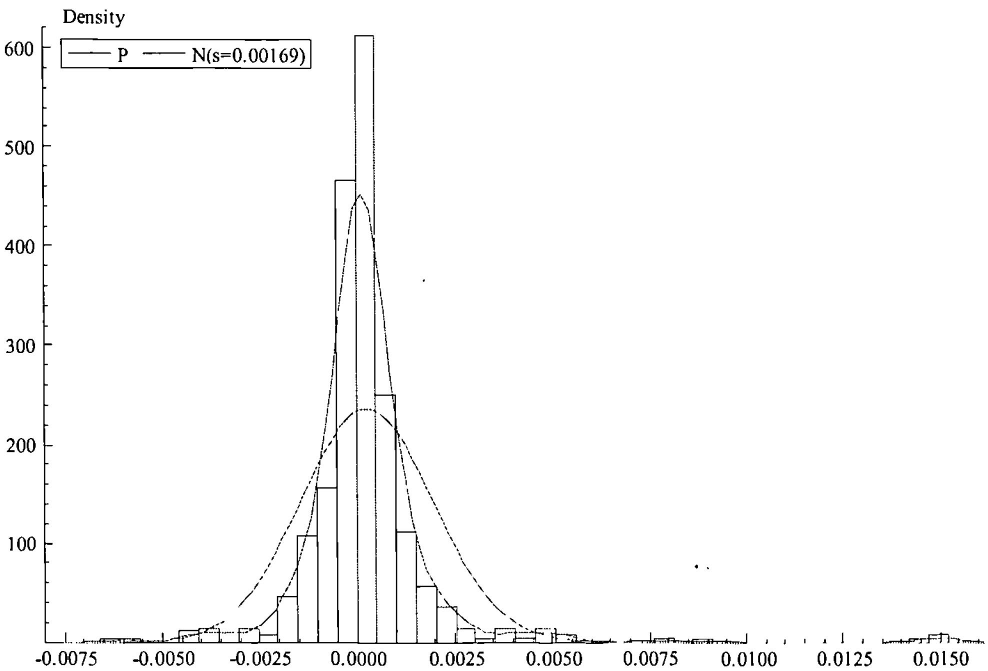


Figure 5.30
Profits For smallest firms (all sample period)

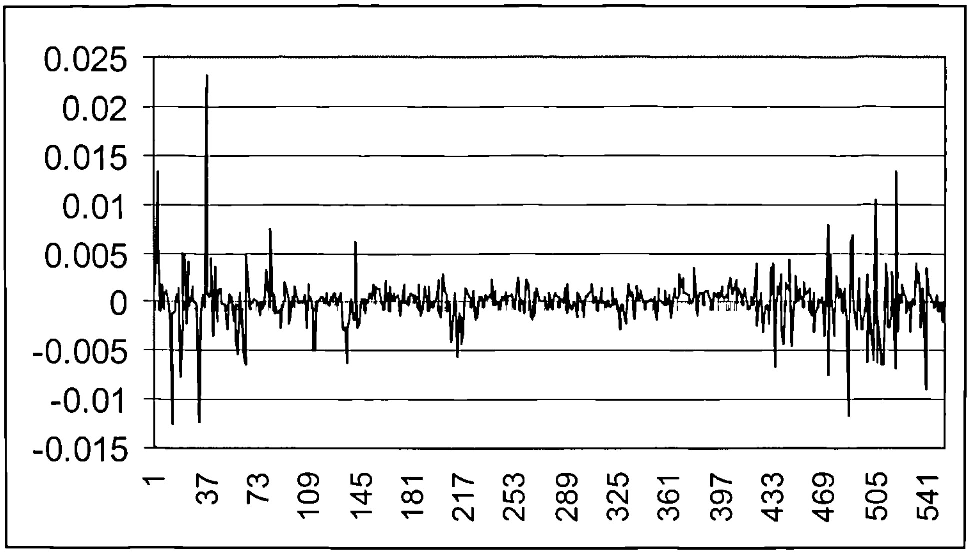


Figure 5.31
Profits For smallest firms Histogram (all sample period)

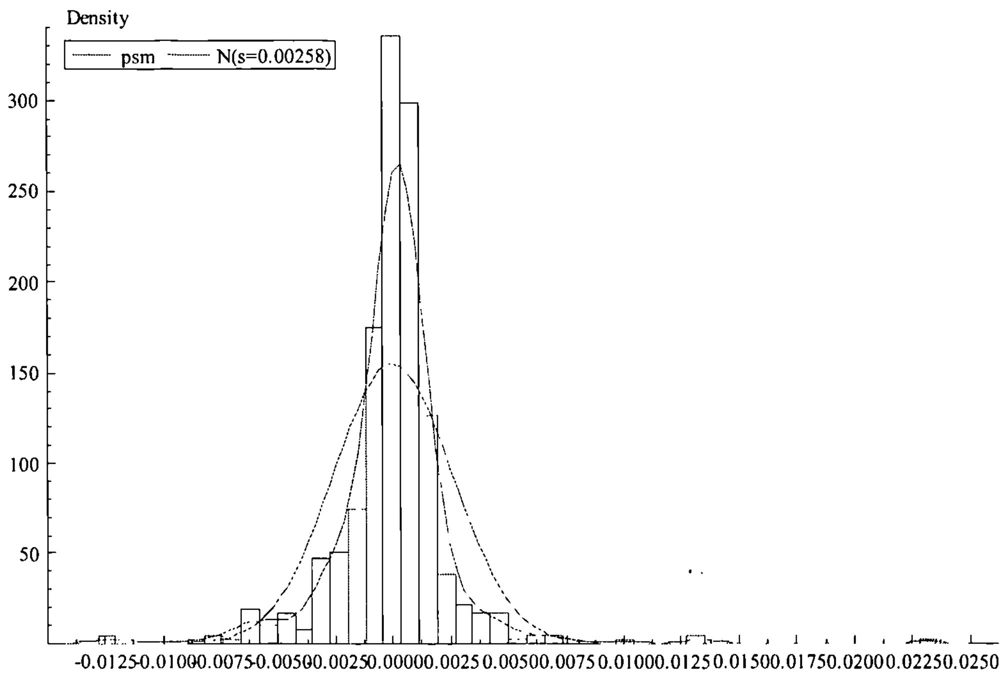


Figure 5.32
Profits For small firms (all sample period)

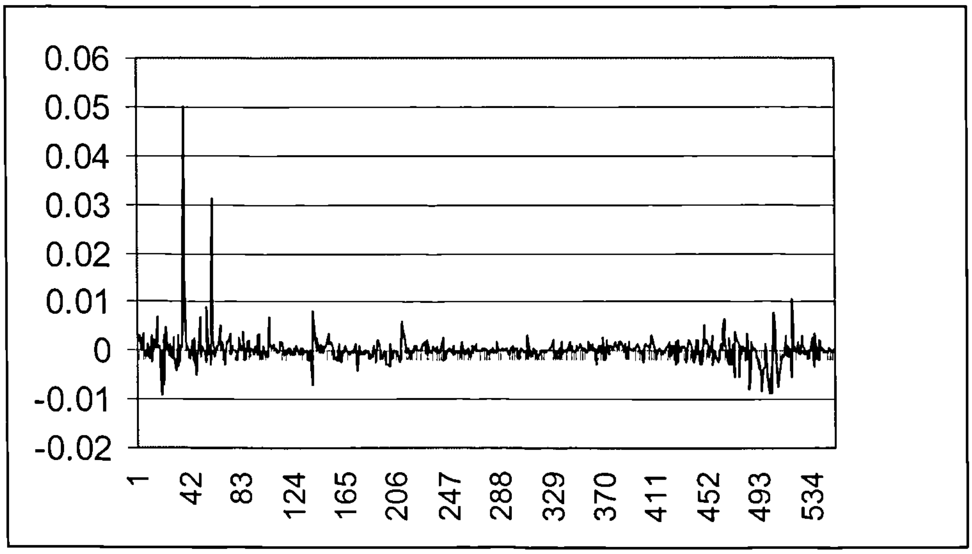


Figure 5.33
Profits For small firms Histogram (all sample period)

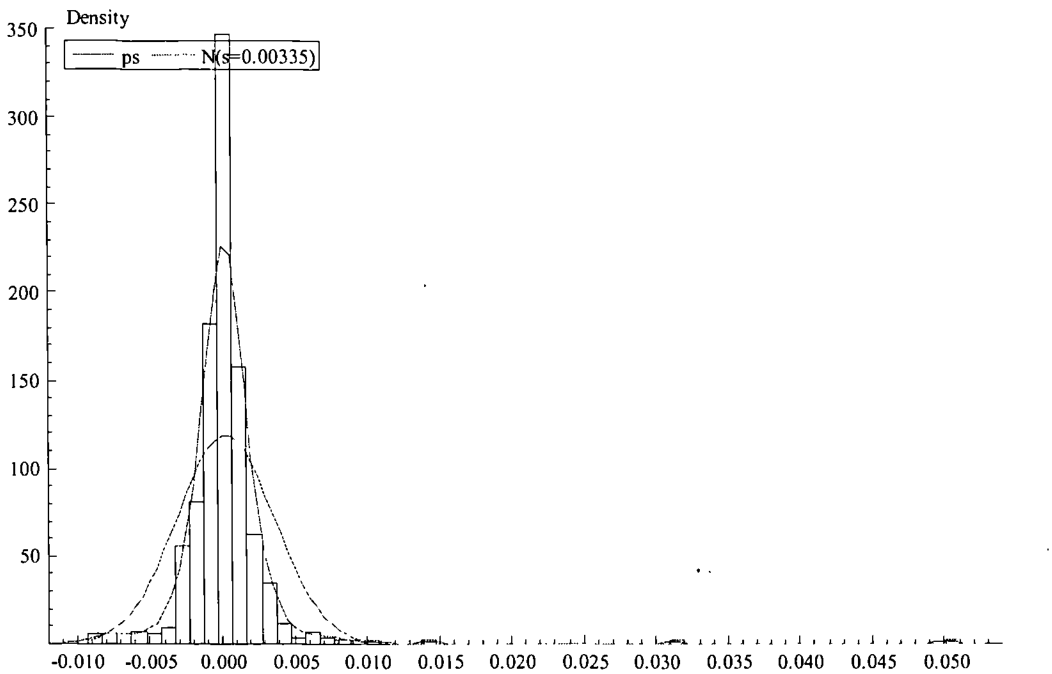


Figure 5.34
Profits For medium firms (all sample period)

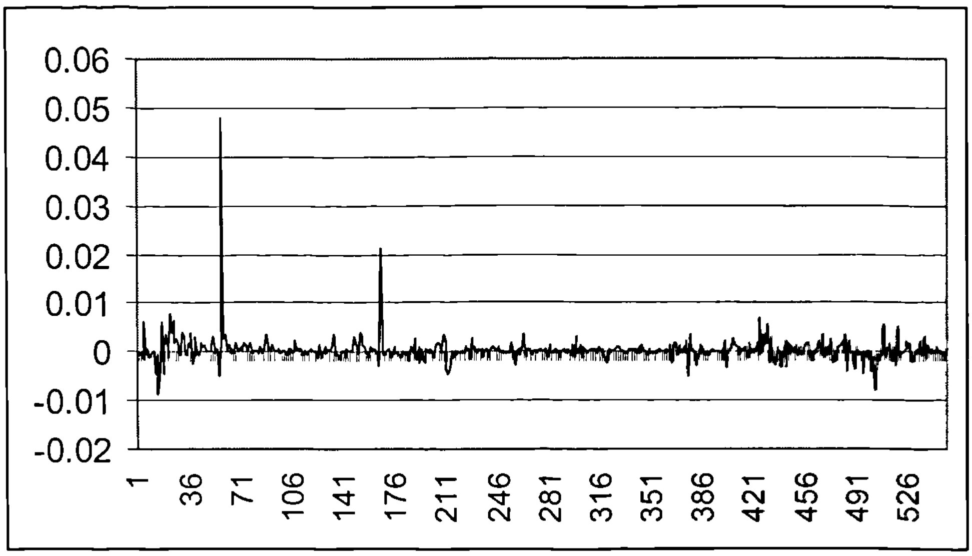


Figure 5.35
Profits For medium firms Histogram (all sample period)

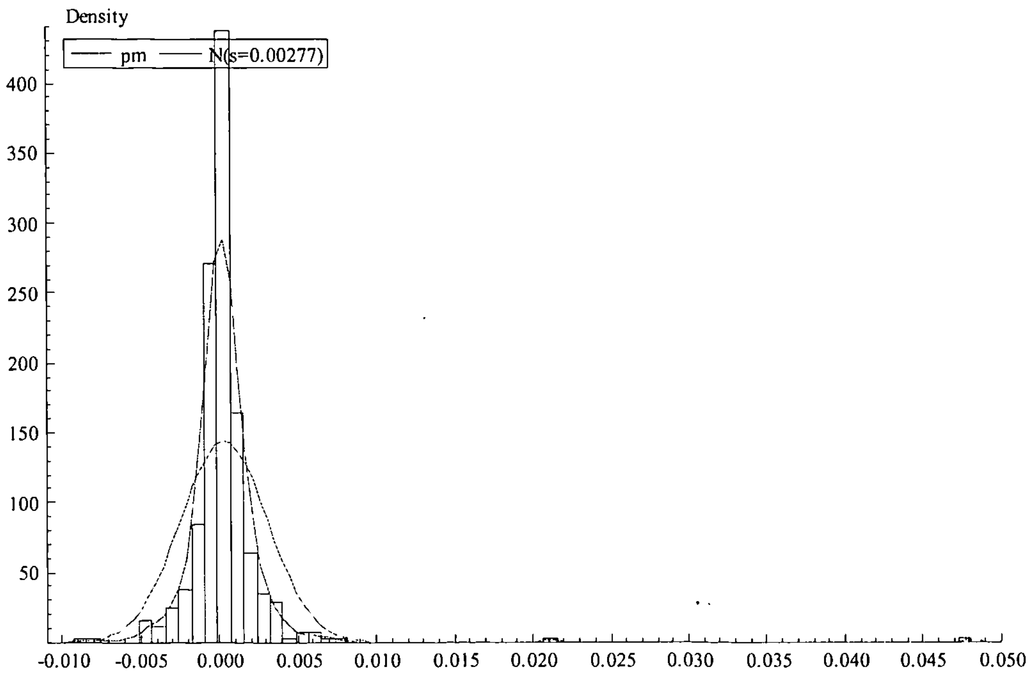


Figure 5.36
Profits For large firms (all sample period)

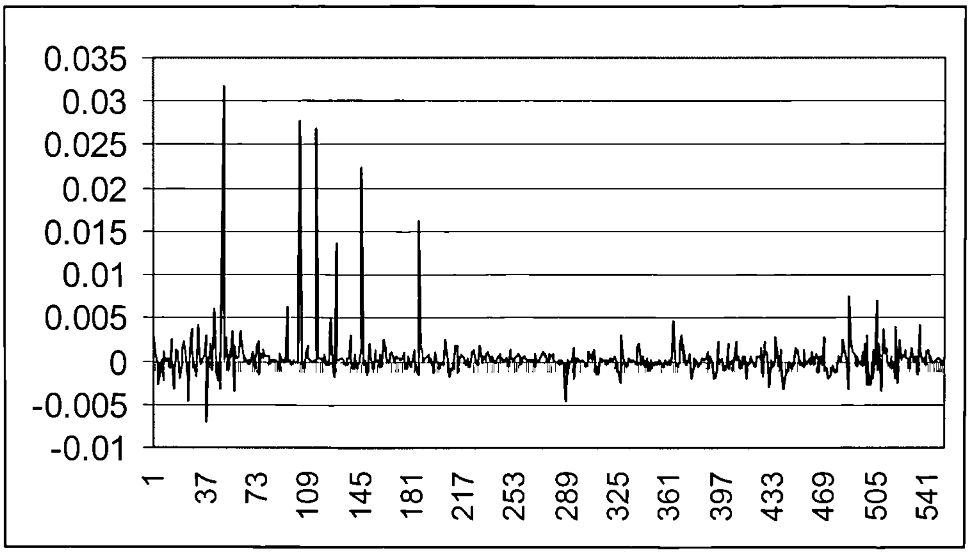


Figure 5.37
Profits For large firms Histogram (all sample period)

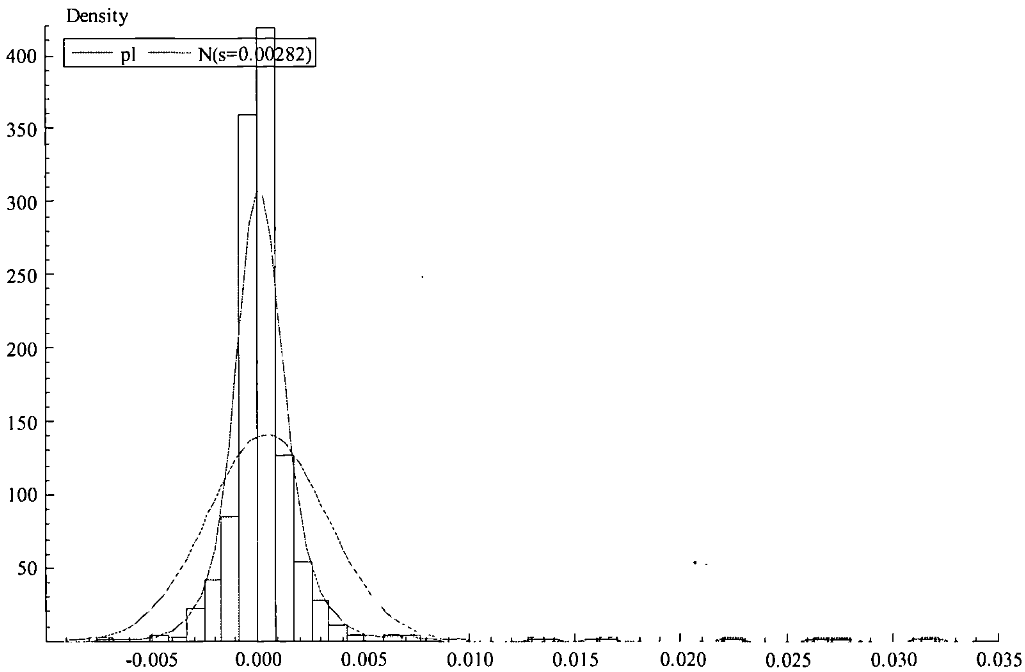


Figure 5.38
Profits For largest firms (all sample period

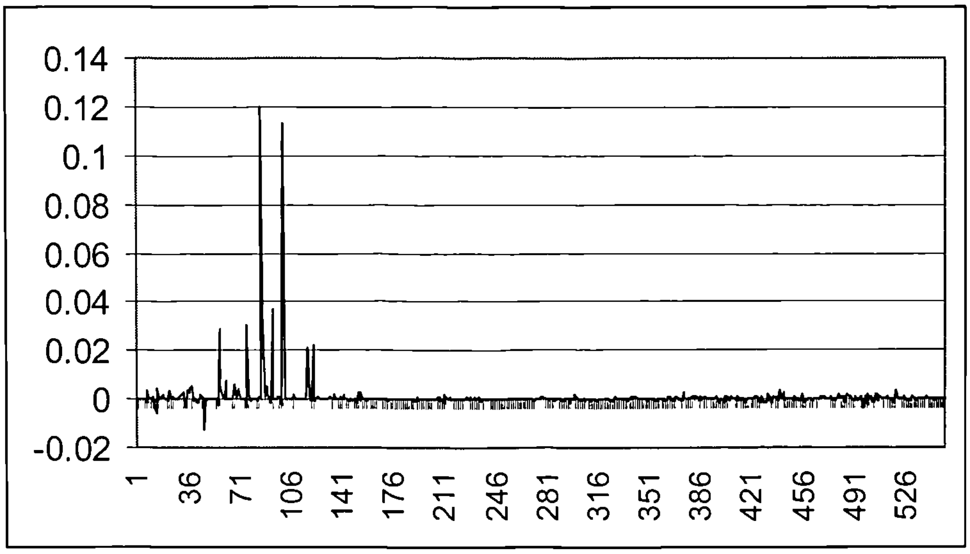


Figure 5.39
Profits For largest firms Histogram (all sample period

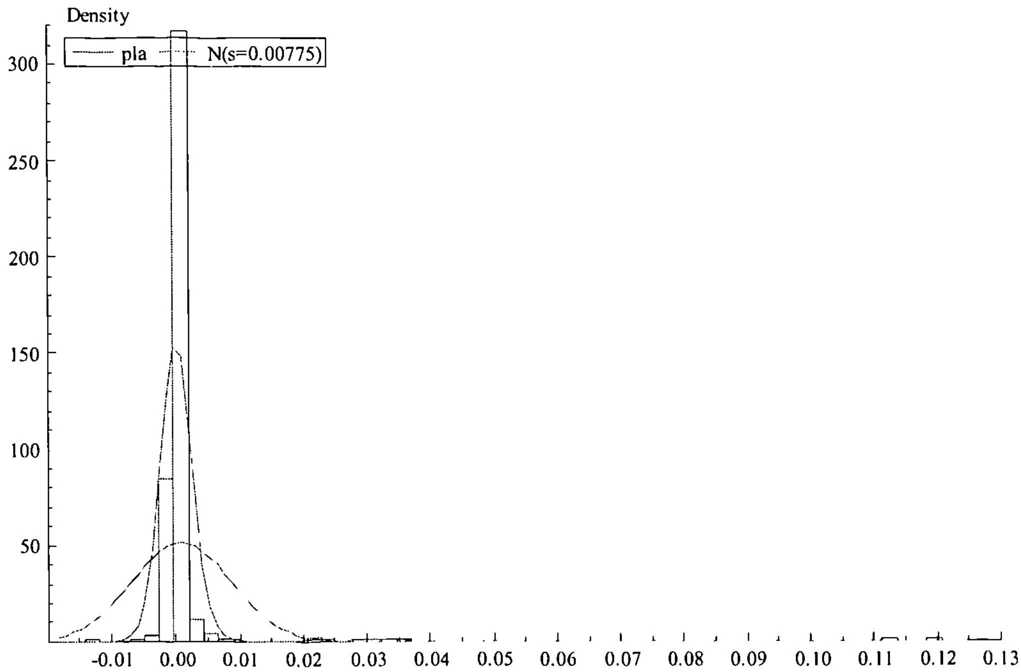


Figure 5.40
SMB Factor Returns (all sample period)

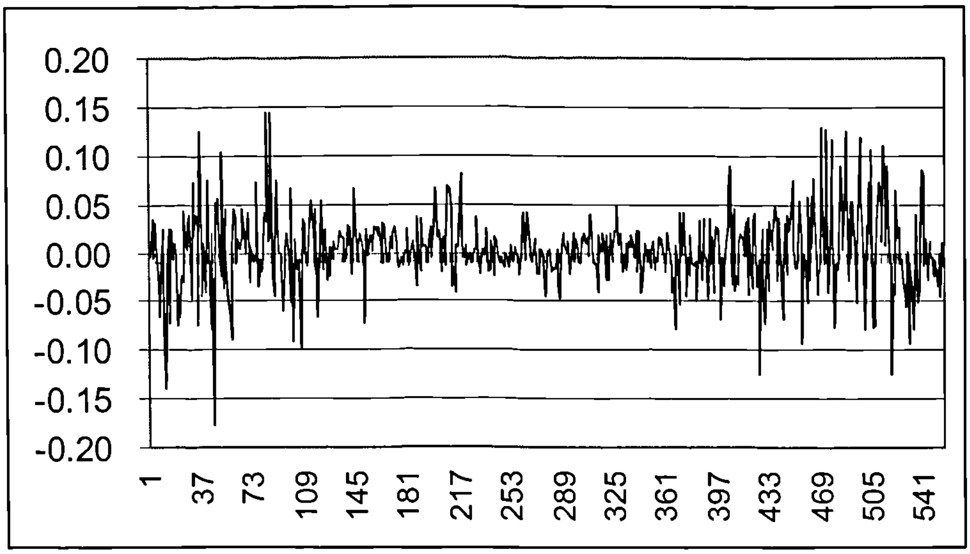


Figure 5.41
Histogram SMB (all sample period)

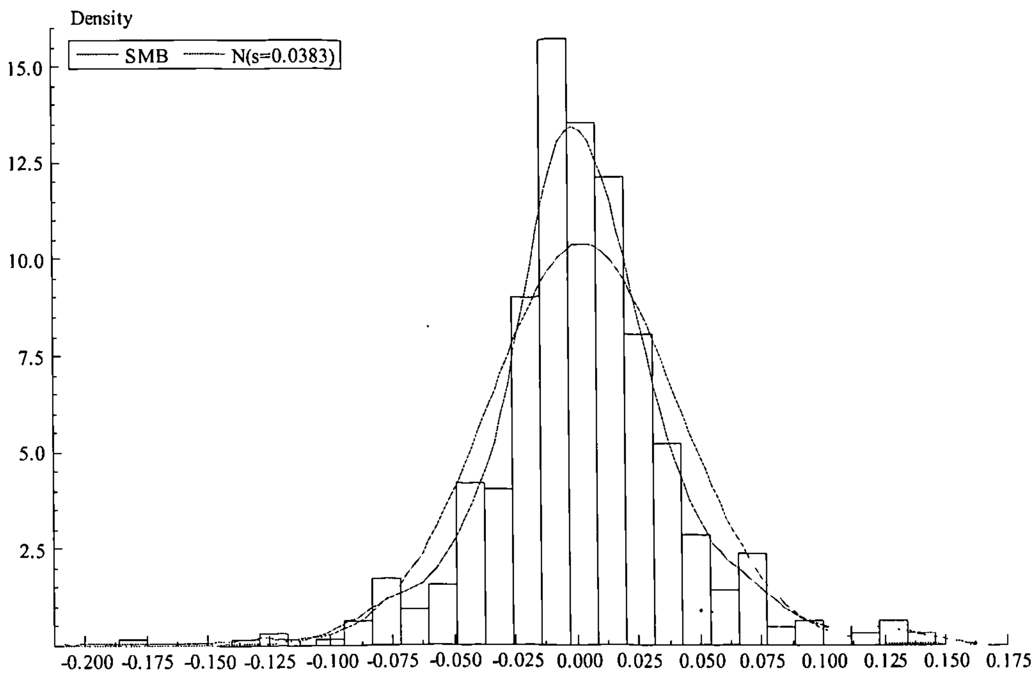


Figure 5.42
HML Factor Returns (all sample period)

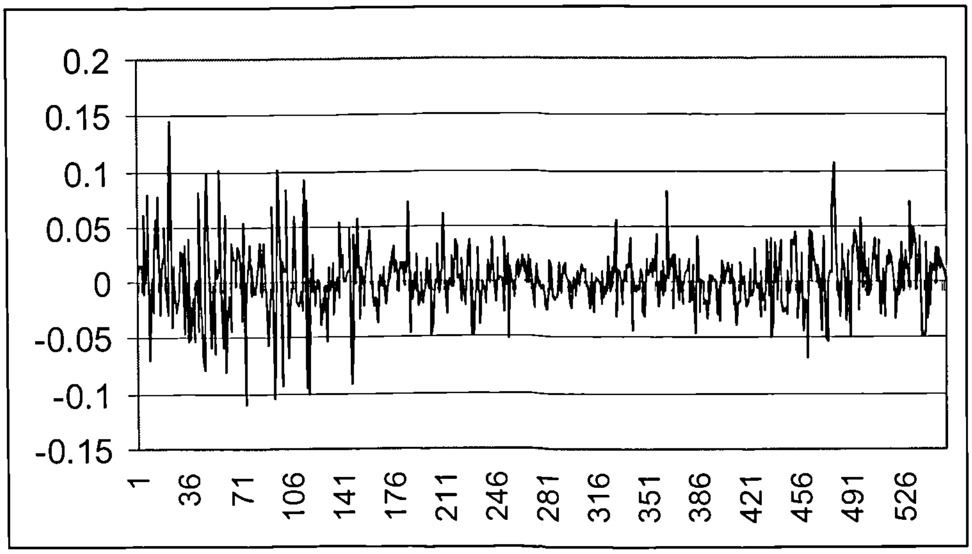


Figure 5.43
Histogram HML(all sample period)

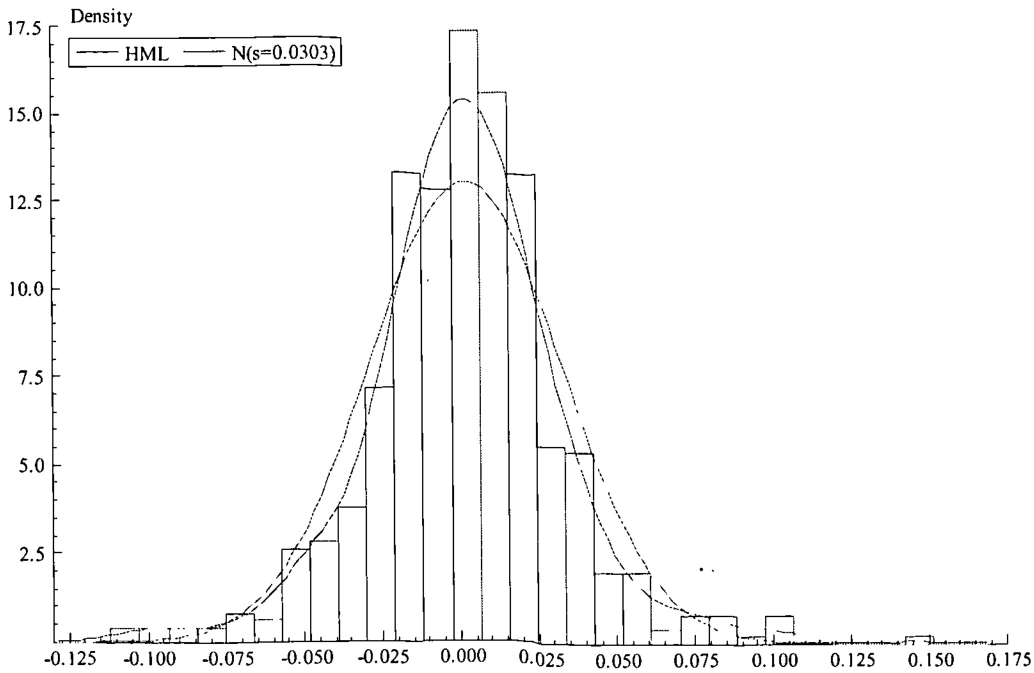


Figure 5.44
Equation (5.8) Residual ACF with theta from one-factor model
(all sample period)

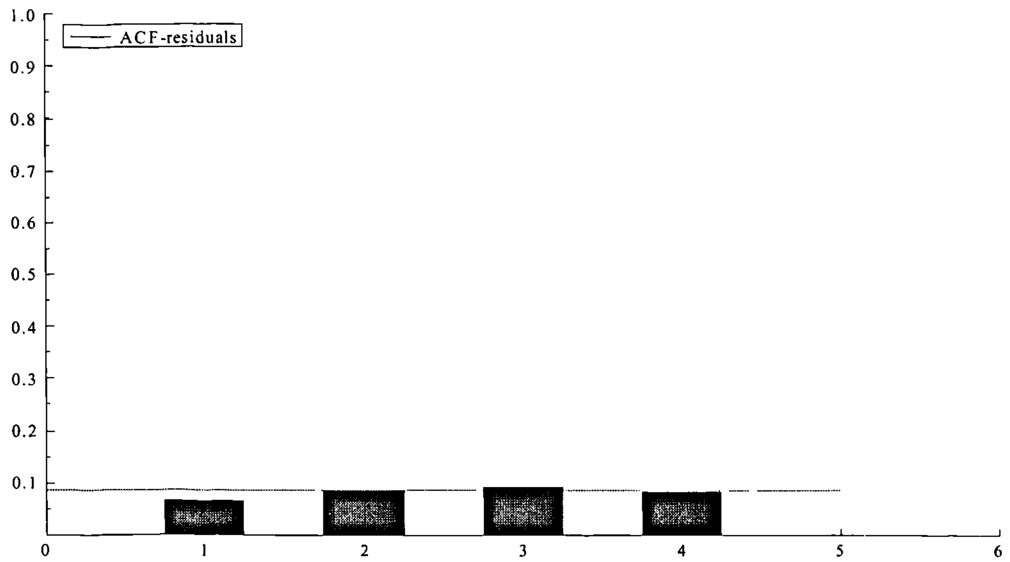
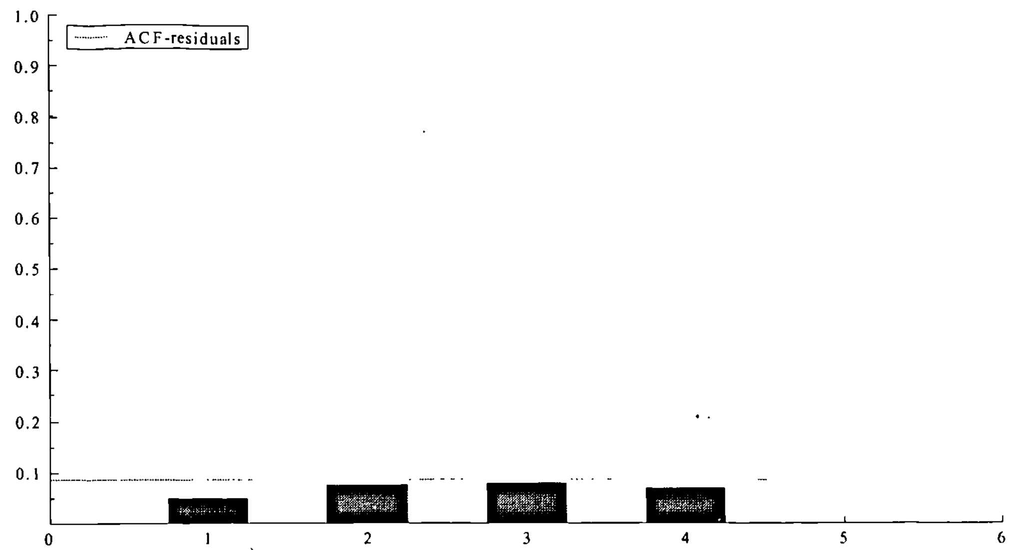


Figure 5.45
Equation (5.8) Residual ACF with thetas from multi-factor model
(all sample period)



Notes to figures 5.44 & 5.45

A very simple test of whether the three-factor model is more efficient than the one-factor model could come from plotting the residual autocorrelation function for each model. However, that would not be efficient here because we estimate them for each stock separately. We then thought that we could perform this test for equation (5.13): $\pi_t = \alpha_0 + \alpha_1 (r_{M,t-1} - \bar{r}_M)^2 + \gamma\theta_{t-1} + u_t$. The only thing that changes in (5.13) when we estimate it using errors from one-factor and multi factor models, is the theta value: $\theta_t = \frac{1}{N}\sum_{i=1}^{N} e_{i,t}^2$.

More specifically, in section 5.3.2 the residuals $e_{i,t}$ come from equation (5.15)

$r_{it} = a_i + b_{0,i} r_{M,t} + b_{1,i} r_{M,t-1} + e_{i,t}$,

While in section 5.3.3 the residuals $e_{i,t}$ come from equation (5.21):

$$r_{it} = a_i + b_{0,M} r_{M,t} + b_{1,M} r_{M,t-1} + b_{0,SMB} SMB_t + b_{1,SMB} SMB_{t-1} + b_{0,HML} HML + b_{1,HML} HML_{t-1} + e_{i,t}$$

Thus, if the three-factor model captures more information than the one factor model, then if we employ the residuals coming from it to create the theta value for equation (5.13), then residuals estimated from equation (5.13) should be lees correlated than the ones coming from estimating (5.13) using residuals from the one-factor model. By looking at the Figures we see that the in the first one the 4 week Residual ACF results cross the 2 standard deviation line, and we thus reject the null hypothesis that the errors are white noise. The same test for the multifactor originated theta factor, shows that we do not reject the null hypothesis of the errors been white noise. Therefore, the errors coming from the multifactor model create a factor (theta) that accounts for more information leaving the residual of equation (5.8) for the first four lags as white noise.

Figure 5.46
Average annual Beta plots smallest firms
(all sample period)

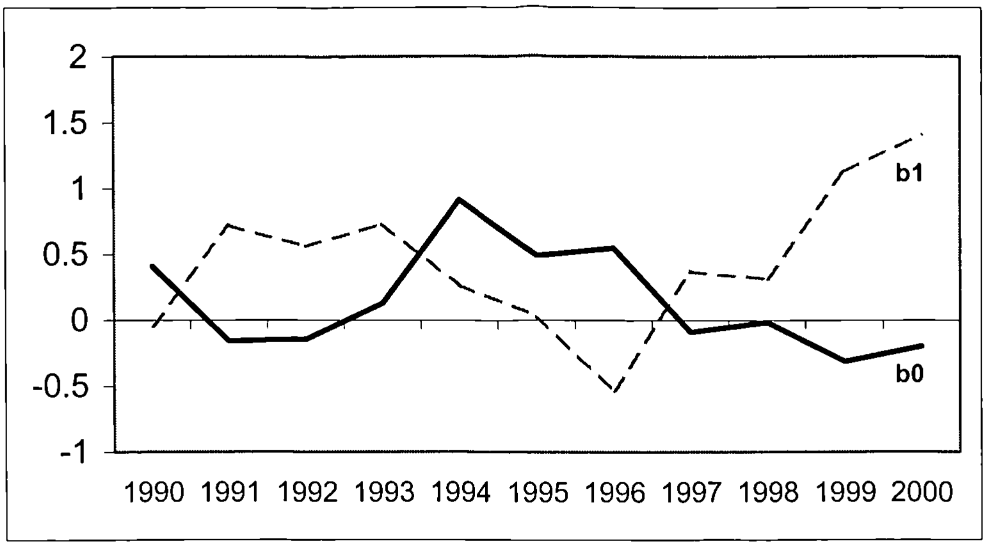


Figure 5.47
Average annual Beta plots small firms
(all sample period)

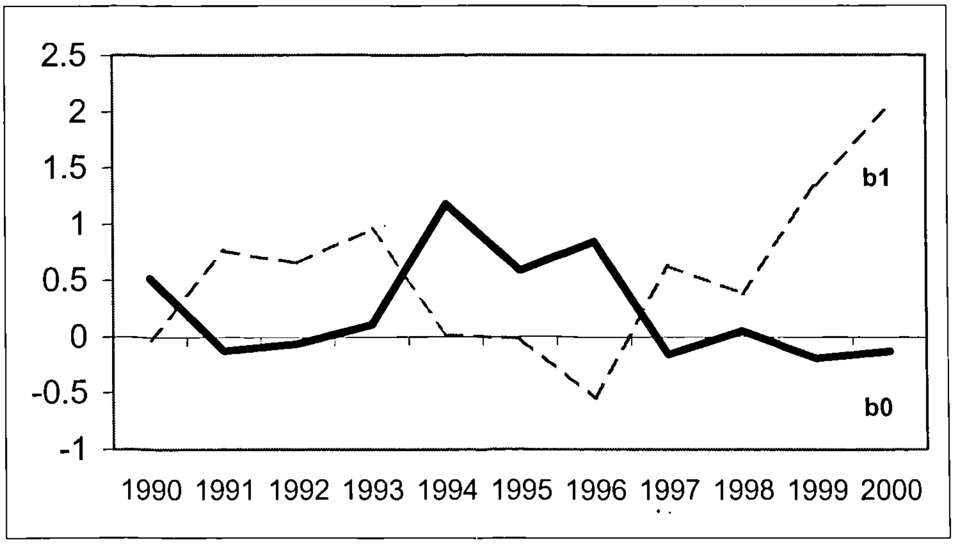


Figure 5.48
Average annual Beta plots medium firms
(all sample period)

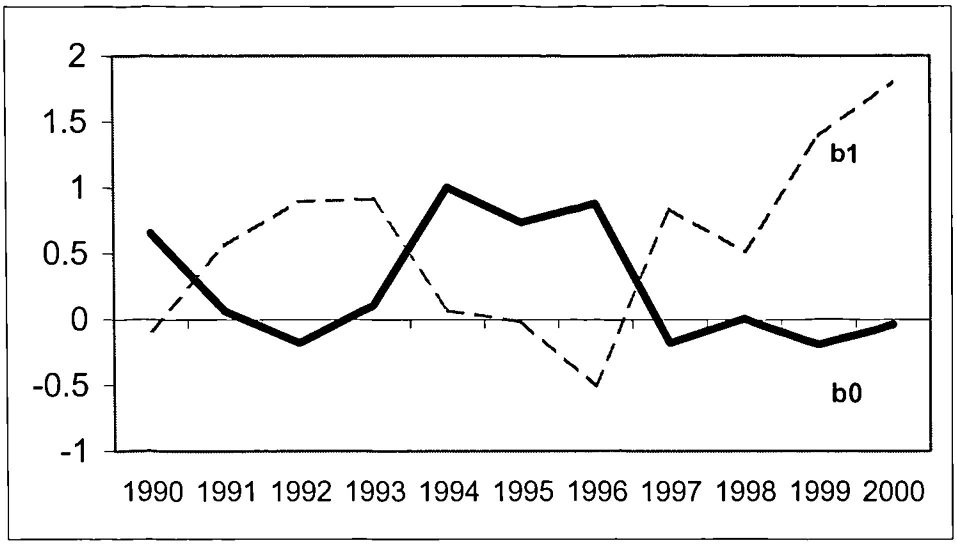


Figure 5.49
Average annual Beta large firms
(all sample period)

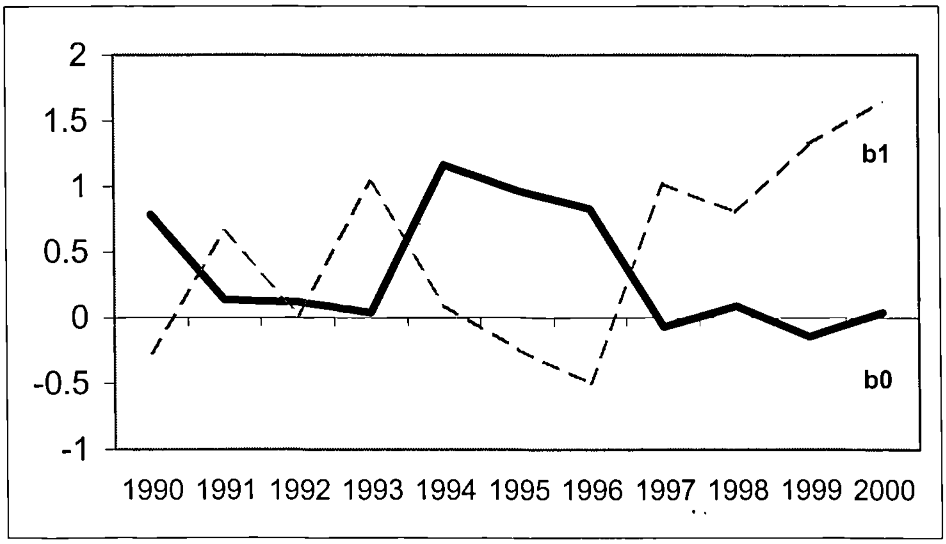


Figure 5.50
Average annual Beta plots largest firms
(all sample period)

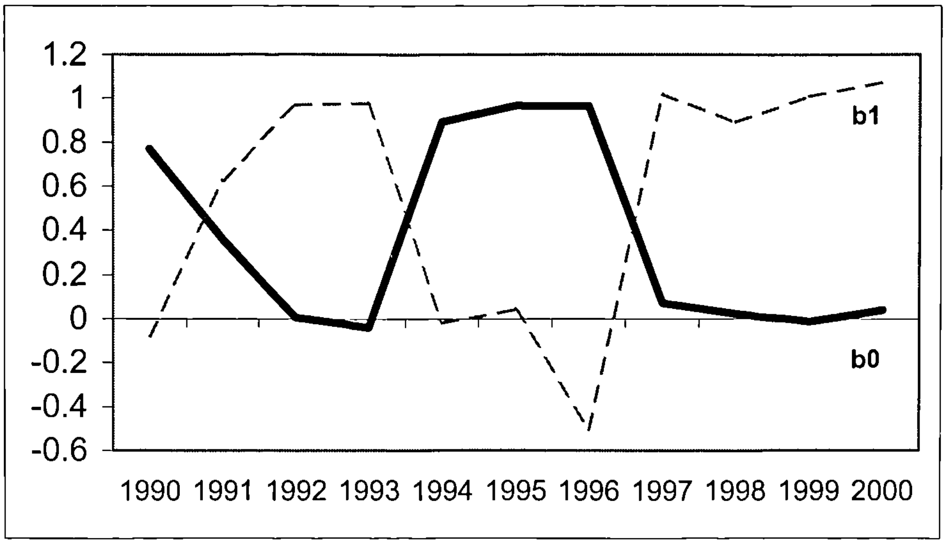


Figure 5.51
Equally-weighted Index Returns Plot (all sample period)

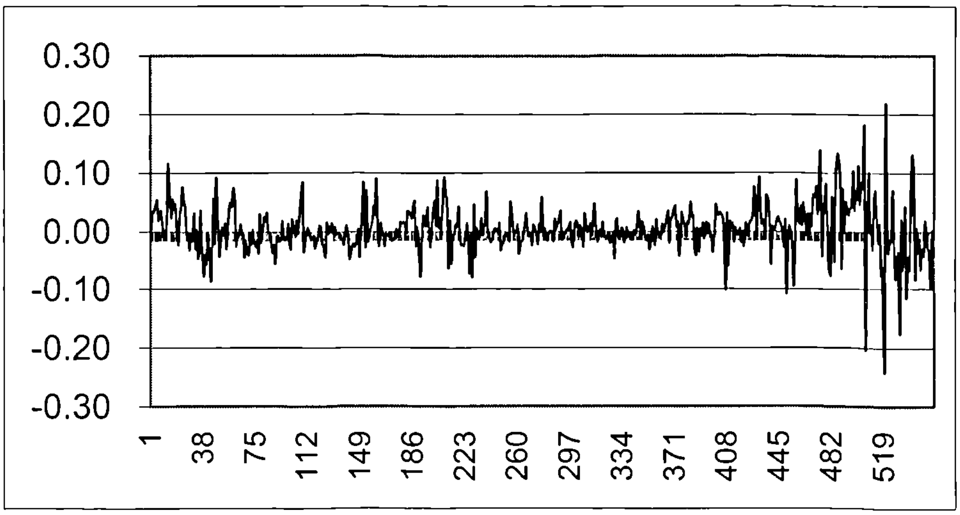


Figure 5.52
Equally weighted Index and ASE GPI Scatter Plot (all sample period)

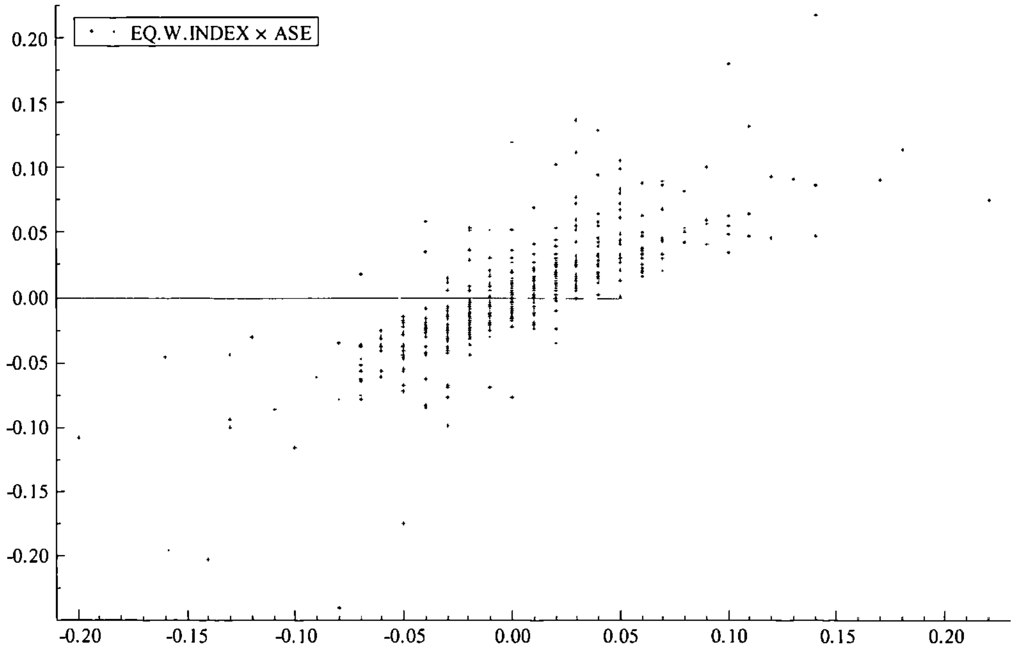


Figure 5.53
Equally weighted Index Returns Histogram (all sample period)

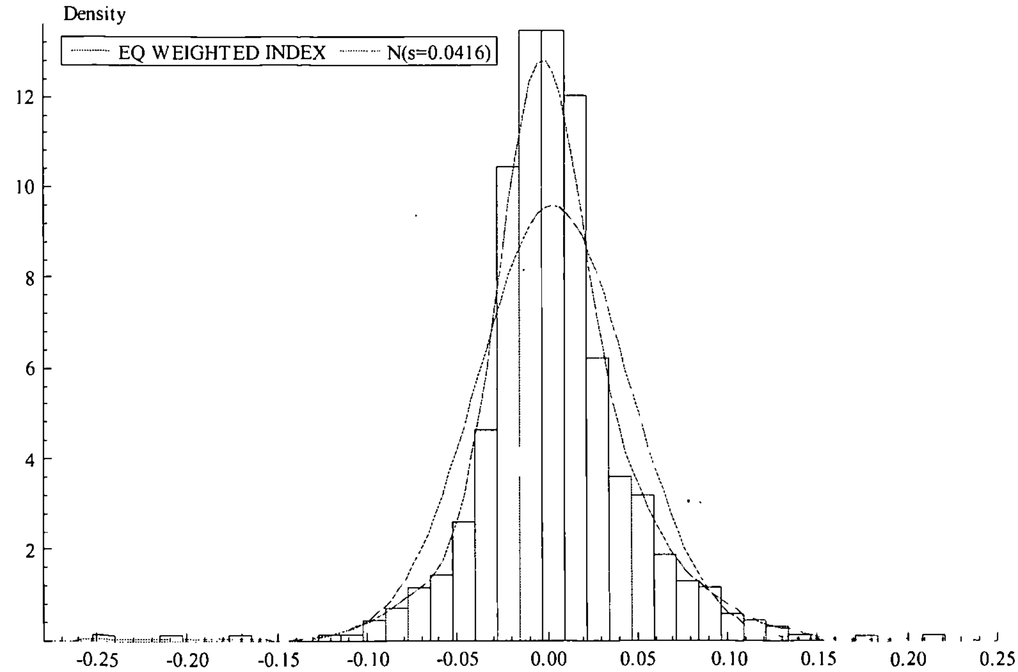


Figure 5.54
Market Value Plot for firm X12

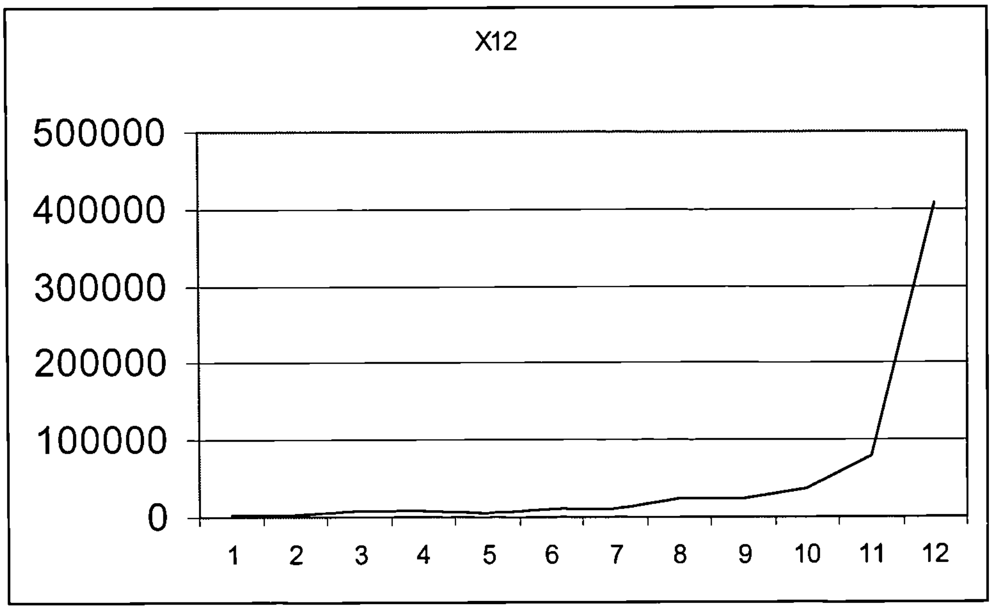


Figure 5.55
Market Value Plot for firm X18

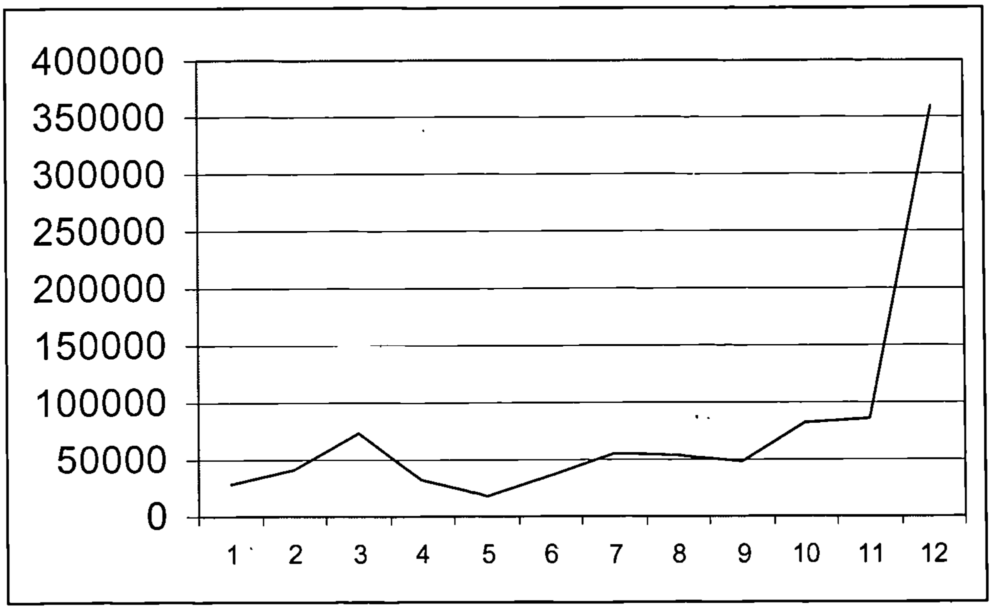


Figure 5.56
Market Value Plot for firm X38

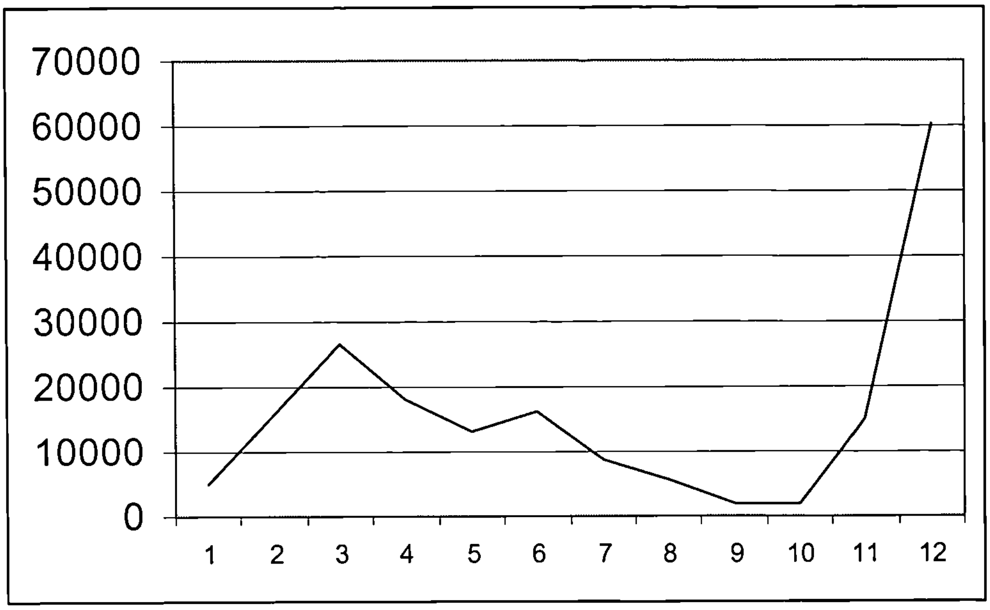
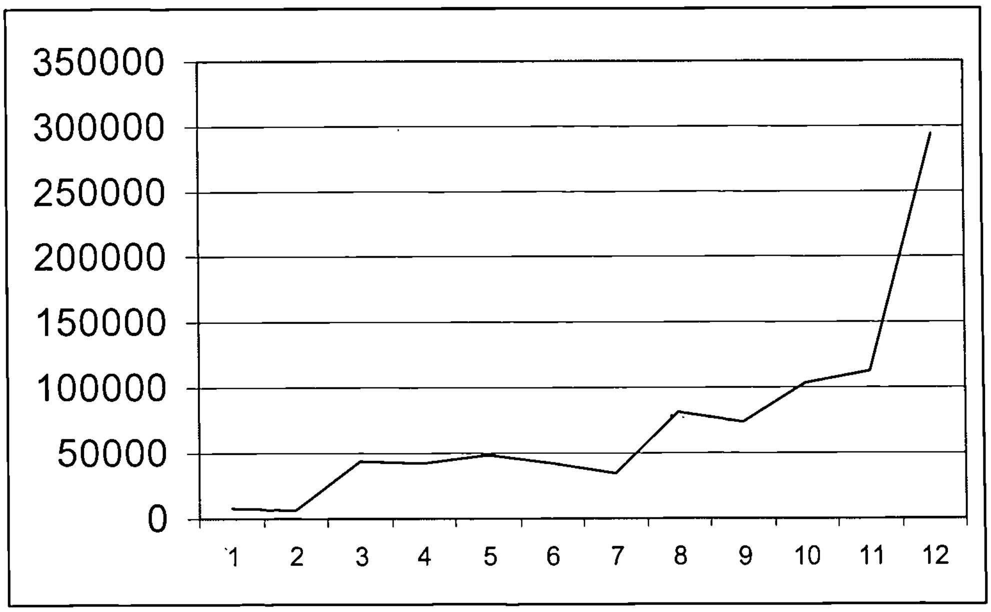


Figure 5.57
Market Value Plot for firm X145



CHAPTER VI.

PROFITS & DECOMPOSITION OF CONTRARIAN INVESTMENT STRATEGIES FOR THE WELL-DEVELOPED UK MARKET; COMPARISONS WITH GREECE

6.1 Introduction

The positive evidence for contrarian strategies observed in the previous chapter could be more pronounced for the particular emerging market data set (for the reasons already explained), or they could be market specific. In addition, chapter II showed that most of the overreaction evidence is related to the US market; less to other markets, and even less when it comes to the UK market, although it is a leading world market. Nonetheless, it is very important to test phenomena that are well documented in the US, using other data as already mentioned, and it is also interesting to compare results of well-developed capital markets with those for less developed ones. The objective of this chapter is to provide evidence for a well-developed market other than the US, and contrast this evidence with the ones from the previous chapter. Given the international importance of the UK market, the little evidence with respect to UK contrarian strategies, and the complete lack of evidence as regards UK short-term contrarian profits and their sources, the thesis is motivated to focus on the London Stock Exchange (LSE henceforth) in the current chapter.

The LSE has been functioning as a regulated exchange since 1801; it is one of the world's leading markets, and the leading European stock market (Clara Furse, Chief Executive LSE, Annual Report 2002). The main market alone offers trading in 2,238 securities, including 447 overseas issuers from 60 countries. In the past year (April 2001 to March the 31st 2002), LSE attracted 66% of all western European IPO's (LSE, Annual Report 2002). Although many empirical studies examine the LSE, there are only a handful of studies when it comes to the issue of overreaction and contrarian strategies. In addition, most of these, are part of a broader study on a number of stock markets (up to eighteen markets) and do not focus in the UK, which limits the depth of empirical evidence as regards the UK stock market. What is of up most importance however is that none of the studies for the LSE considers short-term contrarian strategies, and none of the studies attempts to decompose contrarian profits into common and firm specific factors. However, the identification of the precise source of profits is very important for the success of such strategies, in order to identify the specific factors that are related to the profits and consult these factors to build a profitable strategy. Furthermore, practitioners have nowadays investment-horizons that are not as long-term as earlier studies have assumed; but most practitioners change the components of their portfolios intra-daily, daily or weekly. There are thus gaps in the literature, and in order to cover them, this chapter aims to evaluate the success of short-term contrarian for stocks listed in the LSE, and to identify the sources of these profits.

The methodology used is the same as in the previous empirical chapter that extends the JT (1995) methodology to include among other things a multi-factor pricing model. In addition, tests are repeated with a sample adjusted for infrequent trading and with a sample that uses bid-to-bid rather than closing prices, to determine whether the results are due to the biases analysed in the previous chapters.

To anticipate the results, contrarian strategies appear profitable for UK stocks as well; zero-investment contrarian portfolios that short every week the previous week's winners to long previous losers produce significant profits. Furthermore, like for the ASE, profits persist even after the sample is adjusted for market frictions, such as infrequent trading and bid-ask bias, and irrespective of whether raw or risk-adjusted returns are used to calculate contrarian profits. The profits appear statistically and economically significant, and more pronounced for extreme market capitalization stock portfolios (smallest-largest). In addition, as for ASE, UK stock prices do not fully react contemporaneously to the FF factors, but part of the effect is incorporated in prices with a lag, and these delayed reactions appear to contribute to contrarian profits. Further tests indicate that the magnitude of the contribution of the delayed reactions to contrarian profits is small, while the magnitude of the contribution of investor overreaction to firm specific information to profits is far larger (consistent with JT and the results of chapter V. on ASE). On average, these findings hold for time varying factor sensitivities and even for the single- market-factor model when employed for the decomposition of contrarian profits.

The rest of the chapter is organized as follows: section 6.2 discusses in more detail UK empirical evidence, section 6.3 discusses the data, while section 6.4 reports contrarian profits. Results are presented in section 6.5, and are compared to the ASE results in section 6.6, while section 6.7 concludes the chapter, and section 6.8 is the Appendix.

6.2 Contrarian strategies empirical evidence for UK

Poterba & Summers (1988), find long-term negative serial correlation while testing the overreaction hypothesis for the UK, Canada, US, and fifteen more countries, consistent with contrarian strategies. Dissanaike (1997) following the De Bondt and Thaler (1985) methodology and incorporating the suggestions of Chan (1988), and Ball & Kothari (1989) on risk, employs long term contrarian strategies for the FT500 firms (that includes the largest 500 industrial firms in the UK, and comprises of more than 70% of the LSE market capitalization). His results indicate that not only past losers outperform past winners, but also they are less risky (consistent with De Bondt & Thaler 1985). Brouwer, Van Der Put and Veld (1997) test value strategies in connection to the overreaction hypothesis for the UK, France, Germany and Netherlands for the period 1982 to 1993. They find that past losers (created based on several accounting ratios) outperform past winners for longer-run strategies. Richards (1997) uses data on sixteen national markets including the UK, and finds long-run overreaction profits that are not explained by risk, the January or the size effect. Balvers, Wu, and Gilliland (1999) test for long-term contrarian strategies using data on eighteen countries with developed capital markets -including the UK- for the period 1969 to 1996. Using panel data, Seemingly Unrelated Regression techniques, and the De Bondt & Thaler (1985) strategy, they find positive evidence for mean reversion, consistent with the overreaction hypothesis. Baytas & Cakiki (1999) test the overreaction hypothesis for the period 1982 to 1991, using long-term investment horizons for the UK, Canadian, US, Japanese, German, French, and Italian markets. They find that past losers outperform the market, and past winners under perform the market portfolio, while contrarian arbitrage portfolios have significant and positive profits. However, their results could be due to a masked low-priced-firm effect or size effect as they suggested. The only other study which finds that another explanation than overreaction could be behind UK contrarian profits is that by Claire & Thomas (1995), who test for the UK market using data on 1000 randomly selected stocks for the period between 1955 and 1990. Using De Bondt & Thaler's (1985) methodology, they find long-term (24 to 36 months) evidence consistent with return reversals that are not explained by risk or the January effect. They find however that the results are related to size and most of the outperforming firms are smaller firms.

In summary, although there is international empirical evidence to suggest that contrarian strategies are profitable, there is little evidence for the UK market, and most of it is from studies that focus on many markets simultaneously thus reducing the level of insight that they offer for the UK. In addition, there is complete lack of evidence on short-term contrarian profits and the decomposition of such profits for the UK.

Motivated by the above, and by the need to compare the ASE market results with a more developed market, this chapter uses the UK market as a paradigm of well-developed markets, to test for contrarian strategies.

6.3 Data

The chapter uses weekly price observations for all stocks listed on the London Stock Exchange (LSE) with at least 260 consecutive observations[108] between December 1984 and September 2000. As a proxy for the market portfolio, the FTSE100[109] Price Index is used. Returns are defined as before, and all data are collected from Datastream. Table 6.1, presents descriptive statistics on the number of firms available for each year and the market value of the sample firms. For example, the maximum number of firms available is for year 1990 (1645 firms) while the minimum number of firms available is for year 1985 (1164 firms). The minimum market value of the sample firms is below 0.01 million Sterling for years 1989 through 1996, while the maximum market value is for year 2000 (119,814.1 million sterling). Mean market values range from 255,1624 million (year 1985) to 1,234.571 million (year 2000).

For the empirical analysis, stocks are assigned to five size sorted sub-samples as in the previous chapter. For example, to create the five sub-samples for the year 1997, all 1520 stocks available for this year are sorted according to the closing market value of the previous year (1996) and assigned to the five sub-samples that each contains 20% of firms. This leaves 304 firms in each sub-sample. The procedure is repeated every year, allowing for five size-sorted sub-samples per year, for a period of sixteen years. Tests are then performed on the whole sample as well as on the five size sub-samples.

[108]This avoids downward bias of the autocovariance estimates that is known to occur in small samples.

Table 6.1
Total Number of Firms in the Sample and Market Values per year

Year	Min Value	Max Value	Mean Value	Standard Error	Standard Deviation	Total number of firms
1985	0.03	63908.49	255.1624	64.07501	2186.076	1164
1986	0.03	66349.63	270.0225	61.88033	2185.173	1247
1987	0.04	50232.23	316.029	53.26607	1957.845	1351
1988	0.04	37661.02	310.5211	42.17414	1611.471	1460
1989	<0.01	40510.89	310.9541	41.77737	1654.827	1569
1990	<0.01	42404.25	376.6412	45.0914	1828.844	1645
1991	<0.01	34655.77	313.3649	36.15513	1449.365	1607
1992	<0.01	26962	373.1171	40.5028	1590.477	1542
1993	<0.01	24963.15	455.0192	45.46436	1762.001	1502
1994	<0.01	30041.87	568.5602	54.27537	2116.739	1521
1995	<0.01	28257.65	525.9799	50.66479	2000.457	1559
1996	<0.01	65188.08	640.5103	72.05224	2871.261	1588
1997	0.04	39147.56	640.5264	66.04175	2574.781	1520
1998	0.04	51451.2	795.1016	88.86772	3379.311	1446
1999	0.04	74902.88	882.729	115.0587	4211.842	1340
2000	0.35	119814.1	1234.571	196.3658	6788.124	1195

[109] We use the FTSE100 index because it appears not to be serially correlated according to the Ljung-Box statistic (Probability value: 1st order 0.836, 2nd order 0.188, etc), while this is not the case for the FTSE All-Share Index (Probability value: 1st order 0.033, 2nd order: 0.003 etc).

Descriptive return statistics, based on closing prices, for all sample groupings are presented in Table 6.2 (Panel A). The average weekly return for all stocks is 0.0005 (0.05%) with a standard error of 0.01662, while the highest mean weekly return, is that of the smallest stock sub-sample (0.00101). The largest stock sub-sample has the second highest mean weekly return (0.00089) and the highest standard error (0.01973). Note that the small and medium stock sub-samples have a negative mean weekly return. What is very interesting is that the two extreme size sub-samples have the highest mean weekly returns.

The above statistics might be affected by the way prices are measured (e.g. closing prices, bid or ask prices) as is well documented in the literature. For example Kaul & Nimalendran (1990) find that the bid-ask error component explains over 50% (23%) of small (large) firm variance. In order to investigate whether this problem affects the current sample, bid prices are also used, and in Panel B of the same Table, descriptive statistics based on bid rather than closing prices are reported. The mean weekly return is much lower (0.00029 or 0.029%) and now the smallest, small, and medium stock sub-samples all have negative returns. At the same time the mean return for the large stock sub-sample is virtually unaffected (although its total risk is now much lower) and the return on the largest sub-sample is somewhat reduced. These results suggest that whether one uses closing or bid prices affects the risk and return characteristics of the samples, and could affect results. Thus, the rest of the chapter will examine both closing prices and bid prices (trying to measure the possible bid-ask bias).

Table 6.2
Descriptive Statistics of Stock Returns

	All Stocks	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
			Panel A: Descriptive Statistics (Closing Prices)			
Mean	0.00050	0.00101	-0.00003	-0.00002	0.00048	0.00089
Standard Error	0.01662	0.01784	0.01697	0.01697	0.01796	0.01973
Minimum	-0.16978	-0.14958	-0.17176	-0.16546	-0.17956	-0.18397
Maximum	0.06778	0.07827	0.08295	0.07557	0.09478	0.10306
Skewness	-2.30835	-1.53943	-2.05311	-2.0446	-1.86742	-1.82349
Kurtosis	20.5054	14.00213	18.46336	16.54123	17.78007	18.95179
Jarque-Berra	15149.6	7048.275	12268.07	9956.03042	11318.997	12772.641
			Panel B: Descriptive Statistics (Bid Prices)			
Mean	0.00029	-0.00008	-0.00014	-0.00021	0.00049	0.00062
Standard Error	0.01926	0.000765	0.00071	0.00076	0.00079	0.00082
Minimum	-0.20309	-0.20147	-0.18557	-0.22177	-0.19913	-0.18624
Maximum	0.08144	0.08501	0.06837	0.08443	0.10826	0.11884
Skewness	-2.68446	2.00923	-2.34711	-2.65513	-2.21395	-1.55343
Kurtosis	25.0880	17.62133	18.60344	26.00095	21.34257	14.61788
Jarque-Berra	19746.97	9636.45	10859.65	20775.33	14015.79	6588.39

Notes to Table 6.2:

Returns are continuously compounded, defined as the first difference of the logarithmic price levels and all data are collected from Datastream. Stocks are assigned to five size-sorted sub-samples that contain 20% of firms as follows: every year stocks are ranked on the basis of the previous year-end stock market capitalization. The procedure is repeated every year, allowing for five size-sorted sub-samples per year, for a period of eleven years, from smallest to largest. The "All Stocks" category contains all stocks in the sample.

Next, the existence of serial correlation in UK stock returns (closing prices) is investigated, since negative serial correlation can lead to short-run contrarian profits. For example, a strategy that each period shorts past winners and longs past losers can benefit from first order negative serial correlation in individual stock returns, because this will transform winners to losers and losers to winners, and the contrarian strategy can then delivers profits. Tables 6.3A and 6.3B, look into three different types of returns following the suggestion of Chopra et al. (1992) that the definition of abnormal returns is very important for examining the profitability of contrarian strategies. More specifically, the chapter at this point, does not only examine raw returns (Panel A) but also examines risk-adjusted returns (Panels B and C), using two methods to account for risk. It first considers risk to be related to a common market factor (i.e. a market index) as is usually done in most previous studies. That is, risk adjusted returns are defined as the residuals ($e_{i,t}$) from a market model (see the chapter V., equation 5.4). However, FF (1993,1996) have shown that extending the CAPM to include additional factors explains the US[110]contrarian profits. Thus, this section also examines 3-factor-adjusted returns (Panel C) (from factors created as in the previous chapter) defined as the residuals ($e_{i,t}$) from a model very similar to the FF one (as defined in the previous chapter, equation 5.6).

The results (Table 6.3A) indicate that negative serial correlation is indeed present in the data, even after stock returns are adjusted for risk factors. For example, with raw returns (Panel A) 31.2% to 67.5% of the firms that are present (each year) in the sample on average exhibit negative serial correlation. It is interesting to note that when the sample is adjusted for market risk (Panel B) 643 firms (from 453 for raw returns) exhibit 1st order negative serial correlation, while when returns are adjusted for the three FF factors 739 firms exhibit 1st order serial correlation. In other words, in Panel C more than 50% of firms per annum are on average negatively serially correlated in the first order, 40% of which is significant at the 10% level. The increase in the number of firms that are negatively serially correlated when adjusting for risk using the single factor model, and the further increase realized when using the multifactor

[110] This, according to FF, occurs because past losers are relatively distressed firms, and past winners are stronger firms. That is why past losers have higher expected returns compared to past winners, and their model is able to capture these two qualities. Note however that FF focus on long-term strategies, while the focus here is short-term.

model, can lead to an increase to contrarian profits, since negative serial correlation is positively related to contrarian profits as explained earlier.

Table 6.3A
Serial Correlations & Significance
(All Firms)

	Order of serial correlation			
	1st	**2nd**	**3rd**	**4th**
Panel A: Raw Returns (Stocks with Negative Serial Correlation)				
Number of Stocks	453	621	918	980
5%	119*	219*	424*	491*
10%	153**	282**	507**	567**
Panel B: Risk Adjusted Returns (Stocks with Negative Serial Correlation)				
Number of Stocks	643	813	1018	977
5%	200*	298*	435*	430*
10%	252**	387**	525**	519**
Panel C: Three Factor adjusted Returns (Stocks with Negative Serial Correlation)				
Number of Stocks	739	962	1144	1042
5%	239*	348*	480*	407*
10%	296**	448**	590**	531**

Notes to Table 6.3a:

Firms that have negative serial correlation are reported in the Table.
* denotes firms with significant negative serial correlation at the 5% level
** denotes Firms with significant negative serial correlation at the 10% level
Note also that there are many firms negative serial correlation significant at the 15%.

The results presented above are encouraging for contrarian investment strategies; however, many of the sample firms may trade infrequently and that may be partly responsible for the reported results. Thus, the sample is next adjusted for infrequent trading by removing any firm that does not trade for 4 consecutive weeks (this leaves 660 firms in the sample) and serial correlations are re-estimated and reported in Table 6.3B. Note that many firms still exhibit negative and significant serial correlation. For example, 293 (44%) of the frequently trading firms exhibit negative first order serial correlation when returns are adjusted for the FF factors, 45% of which is statistically significant at the 10% level. Note that for contrarian strategies to work, not all firms in the sample need to be negatively serially correlated. Even if a particular sub-sample exhibits the particular correlation characteristics, the strategy could be employed for this specific sub-sample, while other strategies could be performed on the other samples depending on their characteristics. Furthermore, part of the profits could be related to other factors such as the lead lag effect.

To summarize thus far, it appears that whether one uses closing or bid prices to calculate stock returns may have an effect on the reported results, because the return characteristics of the two samples are different. In addition, negative correlation seems to be present for UK stock returns even when risk is considered by means of various factors. These findings are consistent with Poterba and Summers (1988) that find evidence of negative serial correlation and Balvers, Wu, and Gilliland (1999) who also find evidence of mean reversion.

Table 6.3B
Serial Correlations & Significance
(Frequently Trading Firms)

	Order of serial correlation			
	1st	2nd	3rd	4th
Panel A: Raw returns (Stocks with Negative Serial Correlation)				
Number of Stocks	171	225	354	368
5%	46*	78*	162*	185*
10%	62**	103**	194**	209**
Panel B: Risk adjusted Returns (Stocks with Negative Serial Correlation)				
Number of Stocks	278	333	396	356
5%	100*	133*	179*	157*
10%	121**	173**	221**	196**
Panel C: Three Factor adjusted Returns (Stocks with Negative Serial Correlation)				
Number of Stocks	293	367	425	367
5%	107*	142*	183*	144*
10%	133**	181**	240**	192**

Notes to Table 6.3b:

Firms that have negative serial correlation are reported in the Table.
* denotes firms with significant negative serial correlation at the 5% level
** denotes Firms with significant negative serial correlation at the 10% level
Note also that there are many firms negative serial correlation significant at the 15%.

6.4 Are contrarian strategies profitable in the LSE?

The results of the previous section suggest that the negative serial correlation present in UK equity returns may potentially lead to profitable contrarian strategies. In order to examine whether contrarian profits are present and exploitable, the chapter employs the same methodology as for ASE, where profits for each stock, π_t, are estimated as in the previous chapter (equation 5.1). In addition, the chapter examines the economic significance of such profits per Sterling long (Ψ) as already defined in equation 5.7 (see chapter V. for details).

Table 6.4 reports the average contrarian profit (equation 5.1) and the contrarian profit per Sterling long (equation 5.7) as well as the respective t-statistics (in parenthesis), for all five sub-samples and the full sample. More specifically, Panel A, reports the profits for all sub-samples when closing prices are used to compute returns. As can be seen, contrarian profits are statistically significant for the smallest, large, and largest sub-sample. However, the profits are negative for the large sub-sample. For example, the average weekly contrarian profit ($\pi x10^3$) is 0.1563, -0.0158, 0.0361, -0.0684, and 0.3385 for the smallest, small, medium, large and largest sub-samples respectively. Note that, for the same strategy with US data, JT report average weekly contrarian profits ($\pi x10^3$) of 0.6150, 0.3246, 0.2261, 0.1475, 0.0839, and 0.2619 for similar size groups, respectively. Thus, contrarian profits appear somewhat reduced in the UK. Furthermore, while in the US contrarian profits decline as one moves from small stocks to large stocks, this does not hold for the LSE. Indeed the highest profits are observed for the largest stock group (nearly double of the profits of the smallest size sub-sample).

In order to examine whether the reported contrarian profits and the size-related effect observed above are due to market frictions, such as a bid-ask bias or infrequent trading, the chapter next re-estimates contrarian profits using bid-to-bid prices[111] rather than closing prices (Panel B). In addition, firms that trade infrequently[112] are excluded from the sample, i.e. stocks that do not trade for a consecutive number of weeks (Panel C), although this is a well-developed and active market and such a problem should be less significant. The profits with the bid-to-bid prices appear reduced: the average weekly profit for the all stocks sample from 0.07625 becomes 0.02886 and statistically insignificant. Note though that the average weekly profit for the largest stock sub-sample is still statistically and economically significant but also significantly reduced (0.09572 with bid prices from 0.33848 with closing prices). Thus, it appears that the bid-ask bias may have an effect on results, and may explain a portion of them, but this important point shall be revisited later (particularly in section 6.5.3).

[111] We find bid-to-bid data from the second half of 1986 onward (about a year and a half less then our earlier sample period), thus we sort annual sub-samples starting from 1987. In this case our annual sub-samples are: 384 firms for year 1987, 452 firms for year 1988, 446, 1085, 1111, 1135, 1230, 1315, 1270, 1235, 1135, 1015, and 935 firms for each of the remaining years thereafter. All firms trade frequently and do not suffer from thin trading, and have data for at least 48 out of 52 weeks per annum.

[112] That is, if any of the stocks does not trade for more than 4 consecutive weeks it is removed from the sample for that year. This gives us for 1985 to 2000: 945, 1085, 1230, 1230, 1280, 1150, 1055, 980, 1025, 1100, 1025, 1130, 1155, 1125, 1000, and 945 firms respectively. Distributing these in each size sub-sample between 1985 and 2000, we have 189, 217, 246, 246, 256, 230, 211, 196, 205, 220, 205, 226, 231, 225, 200 and 189 firms respectively. For the all-sample group, we remove stocks that have zero returns for a period longer than six weeks and remove stocks that trade once between months, and as a result, we have 660 firms for that group.

A similar pattern (i.e. lower contrarian profits) emerges when infrequently trading firms are excluded from the sample. For example, the average weekly contrarian profit for the largest stock sub-sample is now 0.10132 from 0.33848 that it was for closing prices (in Panel A) while for the smallest stock sub-sample it is 0.08120 from 0.15630 for closing prices (both statistically and economically significant). These results indicate that part of the contrarian profits could be due to the effect of infrequent trading, but the thesis shall return to this point as well later (particularly in section 6.5.2). It is also interesting to note that, so far, unlike the JT case, profits for medium and large stocks are negative irrespective of how stock returns are estimated, suggesting that contrarian strategies are profitable only for the two extreme size sub-samples (the smallest and largest firm groupings).

Profits might be present and less significant when microstructure biases are considered, however, all the above examined specifications of returns fail to take into account for one important factor: risk. Once risk is considered, it is possible that profits will be insignificant, and therefore, it might be more appropriate to use risk-adjusted returns to estimate profits. As done earlier in this chapter and in chapter V., two procedures are employed to adjust for risk. Firstly, adjustment for market risk is made (equation (5.4)) and the results are reported in Panel D; and secondly adjustment for the FF risk factors is made (equation (5.6)) and the results are reported in Panel E[113]. Results indicate that when a single-factor model is used for risk adjustment, the average weekly profit is statistically significant for all sub-samples except the large sub-sample.

[113] Closing prices, and frequently trading stocks are used as the sample.

Furthermore, contrarian profits seem to decline as one moves from the smallest stock sub-sample to large stock sub-sample, a result more in line with the results for the US market. When the FF factors are employed to adjust for risk, profits for all sub-samples become positive,[114] and statistically significant at the 5% level, and seem to decline as one moves from the smallest stock sub-sample to larger stock sub-samples, contrary to the chapter's earlier findings. Even for the large stock sub-sample profits are now positive. The highest profits are however still the ones of the two extreme sub-samples, with the smallest one experiencing profits that are almost double to the largest stock sub-sample ones.

Hitherto results indicate that contrarian profits are possible in the LSE, and tests suggest that contrarian strategies may produce statistically (π) and economically (ψ) significant profits, irrespective of how stock returns are define. In addition, the two most "profitable" sub-samples appear to be the two extreme sub-samples, i.e. the smallest and largest stocks. Furthermore, once the sample is treated for biases, profits seem to decline as one moves from the smallest stock sub-sample to larger stock sub-samples. The findings are consistent in most cases with the JT ones for the US market, and with long-term profitability findings for the UK (Dissanaike (1997), Van Der Put and Veld (1997), etc).

[114] The increase in profits as one moves from raw returns to single factor adjusted returns, and the further increase for the multi-factor adjusted returns could be related with the increase in the number of stocks that are negatively autocorrelated as we move from one sample to the other (tables 6.3A and 6.3B). Another reason related to the increase in the profits, could be that as will be seen in Table 6.5, all contemporaneous coefficients of the HML factor and some of the SMB factor are negative, which shows that controlling for these variables should increase contrarian profits (see for example Chordia & Shivakumar 2002). Furthermore, if past losers are less risky than past winners (and it is shown here that consistent with De Bondt and Thaler 1985, and Dissanaike 1997, they are indeed less risky), then taking into account for risk should have a positive effect on contrarian profits. The reason is that the loser (winner) risk adjusted profits will be higher (lower).

Table 6.4
Contrarian Profits (π), and £ Profits (Ψ)

	All Stocks	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
	Panel A: Closing prices (all stocks)					
$\pi \times 10^3$	0.07625	0.15630	-0.01585	0.03611	-0.06839	0.33848
	(2.320)*	(2.753)*	(-0.749)	(0.426)	(-4.480)*	(2.495)*
	0.00221	0.00704	-0.00014	-0.00294	-0.00285	0.00487
Ψ	(1.561)	(3.366)*	(-0.121)	(-2.690)*	(-2.675)*	(1.429)
	Panel B: Bid to Bid Prices					
$\pi \times 10^3$	0.02886	0.05741	0.07459	-0.09078	-0.04829	0.09572
	(1.046)	(1.032)	(0.613)	(-5.255)*	(-3.323)*	(5.556)*
	0.00201	0.00168	0.00394	-0.00474	-0.00213	0.00357
Ψ	(0.908)	(1.063)	(0.699)	(-4.032)*	(-1.860)**	(3.035)*
	Panel C: Excluding Stocks that Trade Infrequently					
$\pi \times 10^3$	-0.00127	0.08120	-0.03391	-0.04713	-0.06867	0.10132
	(-0.101)	(1.953)**	(-1.528)	(-2.143)*	(-5.138)*	(7.056)*
	0.00052	0.003325	-0.00117	-0.00420	-0.00210	0.00315
Ψ	(0.574)	(2.265)*	(-0.977)	(-3.502)*	(-2.231)*	(3.656)*
	Panel D: Single Factor Risk Adjusted Returns (Excluding Stocks that Trade Infrequently)					
$\pi \times 10^3$	0.00243	0.21672	0.060575	0.03346	-0.00404	0.11950
	(0.197)	(5.185)*	(2.995)*	(1.703)**	(-0.263)	(8.537)*
	-0.00029	0.00544	0.00289	0.00015	0.00005	0.00332
Ψ	(-0.448)	(4.454)*	(3.169)*	(0.153)	(0.084)	(6.447)*
	Panel E: Three Factor Risk Adjusted Returns (Excluding Stocks that Trade Infrequently)					
$\pi \times 10^3$	0.01777	0.25554	0.09693	0.058466	0.028521	0.12992
	(1.647)**	(6.097)*	(4.874)*	(3.109)*	(1.997)*	(10.369)*
	0.00009	0.00567	0.00381	0.00086	0.00084	0.00368
Ψ	(0.151)	(5.094)*	(4.517)*	(1.007)	(1.369)	(7.938)*

Notes to Table 6.4:

See equation (5.1) for calculation of contrarian profits. Panel A: Results for all firms using closing prices Panel B: Results for all firms using bid-to-bid prices. Panel C: Results after removing firms that trade infrequently. Panel D: risk adjusted returns for frequently trading firms, employing the residual from: $r_{i,t}=a_0+b_{0t}r_{m,t}+e_{i,t}$. Panel E: three factor adjusted returns for frequently trading firms, employing the residual from: $r_{i,t}=a_0+b_0r_{m,t}+b_1SMB_t+b_0HML_t+e_{i,t}$. Contrarian Euro profits (Ψ) are estimated as in equation (5.7). t-statistics reported in parentheses: $t=\frac{\bar{\pi}}{es.e(\bar{\pi})}\sim t_{n-k}$ $t=\frac{\bar{\psi}}{es.e(\bar{\psi})}\sim t_{n-k}$, on repeated sampling (* indicates significance at the 5% level; ** indicates significance at the 10% level).

6.5 Results from the Decomposition of Contrarian Profits

Section 6.4, documented that contrarian strategies are profitable for many sub-samples and for different specifications of UK stock returns. An important question that arises at this stage is related to the sources of these profits. For example, are they due to investor reactions to firm specific information, or are they due to reactions to common factors, i.e. news common to all stocks? The present section proceeds to decompose UK contrarian profits to various sources, in the spirit of chapter V. That is, contrarian profits are decomposed to sources due to common news and firm-specific ones, allowing reactions to these news to be over- or underreactions in each case, facilitating the evaluation of the economic significance of any or either. This is very important since systematic overreaction to firm specific information has been shown to contribute to contrarian profits, while systematic overreaction to common factors could either increase or decrease them. This methodology also allows us to evaluate the extent to which over- or under-reaction to firm specific information has the same impact on contrarian profits as the delayed reaction to common factors, as explained in previous chapters.

Briefly, the chapter employs the same methodology as in the chapter V. for the decomposition of contrarian profits, using a *K*-factor model (eq. 5.10) to describe stock returns. Contrarian profits are decomposed to the cross-sectional variance of expected returns, the negative of the average serial covariance of the idiosyncratic component of returns , and to a component due to differences in the timeliness of stock price reactions to common factors (eq. 5.12-5.19).

6.5.1. Results using all stocks in the sample (closing prices)

As discussed in the introduction, one of the chapter's contributions is the investigation of whether market frictions have an effect on UK contrarian evidence. Thus, as a first step, contrarian profits are decomposed using all stocks in the sample and closing prices, while the following sub-sections decompose profits with a sample adjusted for infrequent trading and with bid prices, in order to assess whether these biases impact the profit decomposition.

Tables 6.5-6.7 report the results of the decomposition of contrarian profits based on closing prices as described in the previous chapter. More specifically Table 6.5 reports the results from estimating equation (5.20) separately for the full sample, and for all stocks in each sub-sample and each year. Columns 1 & 2, report the average sensitivities of stock returns to the current and lagged factor realizations, respectively; and column 3 reports the estimate of the cross-sectional covariance (δ). It can be seen that the average slope coefficient on the contemporaneous market factor is 0.555 and for the lagged market factor is 0.173, suggesting that UK equity returns react more strongly to contemporaneous market factor realizations. This is true for all sub-samples and the reactions are statistically significant. However, stock prices partly react to common factors with a lag (i.e. there is an indication of delayed reaction that could lead to a lead-lag effect). With respect to the other two factors, UK equity returns also seem to react more strongly to the contemporaneous SMB factor (average slope coefficient 0.308) rather than the lagged SMB factor (average slope coefficient 0.033).

The smaller sub-samples react to the contemporaneous SMB factor much stronger, indicating their stronger relationship with this risk premium compared to larger stocks. For both current and lagged SMB realizations, the reactions are also statistically significant. As regards to the HML factor, UK equities react weakly to lagged factor realizations and strongly and negatively to current factor realizations. The cross-sectional covariance is negative ($\delta < 0$) for all sub-samples as regards the SMB and HML factors, indicating that (delayed) reactions to these factors could contribute positively to contrarian profits in LSE. However, δ is positive for most sub-samples for the market factor, indicating that reactions to this factor could potentially contribute negatively.

Table 6.6 provides an estimate of the contrarian profits that are due to each of the three factors ($-\hat{\delta}\sigma_f^2 \times 10^3$, where f = M, SMB, HML). As discussed earlier, when the average sensitivity to the lagged factor is positive (as in Table 6.5) the contribution of the factor reactions to profits is due to delayed reaction. Also, the table provides an estimate of the profits that are due to overreaction to firm-specific information (-Ω), and the unexplained part of the profits ($-\sigma_a^2$). It can be seen that delayed reaction contribution to profits from all three factors is relatively small. For the all stocks sample, it is 0.00004 for the market factor, 0.009 for the SMB factor, and 0.003 for the HML factor and it is higher on average for smaller stocks. Note also that it is negative for most sub-samples as regards the market factor (i.e. reactions to this factor contribute negatively to contrarian profits). However, the contribution to profits due to overreaction to firm-specific info is much higher: 0.069 for the all-stock sample, and it grows as one moves from large to small stocks, consistent with JT.

Table 6.5
Average estimates of stock return sensitivities (3 factors - all stocks)

	$\bar{b}_{o,M}$	$\bar{b}_{1,M}$	$\hat{\delta}_M$
Smallest Stocks	0.645805	0.139315	0.030969
	(38.313)*	(9.564)*	
Small Stocks	0.517984	0.179426	0.029238
	(42.459)*	(17.164)*	
Medium Stocks	0.515874	0.205527	0.010743
	(45.940)*	(21.967)*	
Large Stocks	0.512568	0.221385	0.039508
	(51.945)*	(26.204)*	
Largest Stocks	0.583226	0.119636	-0.04126
	(57.963)*	(14.508)*	
Average	**0.555091**	**0.173058**	**0.0138396**
All Stocks	0.625758	0.217838	-0.000081
	(72.999)	(40.984)*	
	$\bar{b}_{o,SMB}$	$\bar{b}_{1,SMB}$	$\hat{\delta}_{SMB}$
Smallest Stocks	0.777966	0.045671	-0.37027
	(35.275)*	(2.299)*	
Small Stocks	0.450008	0.065278	-0.17492
	(27.278)*	(4.285)*	
Medium Stocks	0.375741	0.040581	-0.11955
	(25.846)*	(2.948)*	
Large Stocks	0.172548	-0.006644	-0.10118
	(13.122)*	(-0.548)*	
Largest Stocks	-0.233638	0.020433	-0.10900
	(-19.566)*	(2.003)*	
Average	**0.308525**	**0.033064**	**-0.17498**
All Stocks	0.3753162	0.032499	-0.04100
	(30.917)*	(4.416)*	
	$\bar{b}_{o,HML}$	$\bar{b}_{1,HML}$	$\hat{\delta}_{HML}$
Smallest Stocks	-0.17028	0.047119	-0.36745
	(-6.272)*	(1.859)**	
Small Stocks	-0.154438	0.008381	-0.15711
	(-7.599)*	(0.440)	
Medium Stocks	-0.214113	0.036601	-0.10690
	(-12.260)*	(2.291)*	
Large Stocks	-0.192566	0.010898	-0.07827
	(-12.207)*	(0.763)	
Largest Stocks	-0.175245	0.047428	-0.14577
	(-12.348)*	(3.782)*	
Average	**-0.181328**	**0.030086**	**-0.1711**
All Stocks	-0.143107	0.025595	-0.01442
	(-12.685)*	(3.549)*	

Notes to Table 6.5:

The coefficients $\bar{b}_0$ and $\bar{b}_1$ are obtained from equation:

$$r_{it} = a_i + b_{0,M} r_{M,t} + b_{1,M} r_{M,t-1} + b_{0,SMB} SMB_t + b_{1,SMB} SMB_{t-1} + b_{0,HML} HML + b_{1,HML} HML_{t-1} + e_{i,t}$$

which is estimated for the full sample, and for each year, each stock, and each sub-sample separately. SMB is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and HML is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks. This provides estimates of α_i, b_0, b_1, for the full sample, and for each year, each sub-sample, and each factor. Then, $\bar{b}_0$ and $\bar{b}_1$ are calculated as the averages of b_0 and b_1.
(* indicates significance at the 5% level. ** indicates significance at the 10% level)

Table 6.6
Decomposition of contrarian profits (3 factors - all stocks)

	$-\hat{\delta}\sigma^2_M$ x10^3	$-\hat{\delta}\sigma^2_{SMB}$ x10^3	$-\hat{\delta}\sigma^2_{HML}$ x10^3
Smallest Stocks	-0.014620	0.085752	0.078105
Small Stocks	-0.013803	0.040511	0.033395
Medium Stocks	-0.005071	0.027686	0.022722
Large Stocks	-0.018651	0.023433	0.016638
Largest Stocks	0.019477	0.025245	0.030985
All Stocks	0.000038	0.009496	0.003065
	-Ω x10^3	$-\sigma^2_a$ x10^3	
Smallest Stocks	0.240971	-0.207935	
Small Stocks	0.110115	-0.151600	
Medium Stocks	0.033356	-0.129992	
Large Stocks	0.015432	-0.108121	
Largest Stocks	0.097521	-0.073256	
All Stocks	0.069006	-0.016238	

Notes to Table 6.6:

The term $-\hat{\delta}\sigma^2_M$ provides an estimate of the part of contrarian profits due to market reactions. The term $-\hat{\delta}\sigma^2_{SMB}$ provides an estimate of the part of contrarian profits due to reactions to the size factor, while the term $-\hat{\delta}\sigma^2_{HML}$ provides an estimate of the part of contrarian profits due to reactions to the book-to-market factor. The negative of the average autocovariance of the error term, Ω, defined as $\Omega \equiv \frac{1}{N}\sum_{i=1}^{N} \text{cov}(e_{i,t}, e_{i,t-1})$, provides an estimate of contrarian profits due to overreaction to firm-specific information. The negative of the cross-sectional variance of expected returns ($-\sigma^2_a$) provides an estimate of the profits that are not due to the previous terms.

In order to account for possible time variation in factor sensitivities the chapter applies the decomposition of profits as described in equations (5.16 to 5.19). Note that to create the firm-specific related factor (θ_t), the estimated residuals from equation (5.20) are employed. The results are presented in Table 6.7 (Panels A and B). The slope coefficients (α_1, α_2, and α_3) provide an estimate of the contrarian profits due to the reactions to the market, SMB, and the HML factors respectively, and the coefficient (γ) provides an estimate of profits due to overreaction to firm-specific information (Panel A). It can be seen that they are statistically significant for most sub-samples and the all-stock sample, however the market factor estimates are negative.

Panel B provides estimates of the contrarian profits due to delayed reactions to common factors (i.e. the product of the coefficient with the variance of each factor) and overreaction to firm specific information. For example, the contrarian profit for the smallest stock sub-sample due to firm-specific overreaction (last column in Panel B) is 0.073. Since the average weekly contrarian profit for this sub-sample is 0.156 (Table 6.4, Panel A, 2nd column) the contrarian profit due to firm-specific overreaction should be the ratio 0.073 / 0.156 = 0.467. In other words, 46.652% of contrarian profits for the smallest stock sub-sample are due to firm specific overreaction. This ratio is provided in the table for all sub-samples and factors in brackets. For example, for the all-stock group, 121.959% of contrarian profits appear to be due to firm-specific overreaction, 24.307% due to delayed reaction to the HML factor, 46.572% due to delayed reaction to the SMB factor, and -40.314% due to reaction to the market factor. Note that, for the US and the all-stock sample, JT find the contribution of firm specific information to contrarian profits to be approximately 104%. The fact that the factors (common and firm specific) currently in the model contribute together about 150% of contrarian profits for the all-stock sample shows that there might be some other factors not described in the model that contribute negatively (-50%). Another explanation however, could be that not correcting for microstructure biases has affected the decomposition, but that is to be seen in the two following sections that deal with such issues.

Table 6.7
Decomposition of contrarian profits with time-varying factor sensitivities
(3 factors - all stocks)

Panel A: Estimated coefficients

	α_0 x 10^3	α_1 x 10^3	α_2 x 10^3	α_3 x 10^3	γ x 10^3
Smallest Stocks	0.05662 (0.840)	-40.04323 (-1.045)	104.87354 (0.918)	104.76158 (2.455)*	17.53029 (2.949)*
Small Stocks	-0.01593 (-0.677)	-87.06687 (-6.507)*	118.18356 (2.961)*	109.20998 (7.327)*	-2.44207 (-1.176)
Medium Stocks	-0.05919 (-2.670)*	-48.28303 (-3.829)*	29.96345 (0.797)	114.94104 (8.183)*	1.057801 (0.541)
Large Stocks	-0.07135 (-4.408)*	-39.49639 (-4.291)*	47.23366 (1.721)**	38.70094 (3.774)*	-2.57271 (-1.801)**
Largest Stocks	0.14647 (0.923)	-46.69936 (-0.519)	234.44236 (0.873)	27.37841 (0.273)	38.07464 (2.719)*
All Stocks	-0.03938 (-1.079)	-64.98927 (-3.060)*	153.04215 (2.414)*	87.02743 (3.719)*	22.31376 (6.835)*

Panel B: Contributions to contrarian Profits

	$\alpha_1\sigma_M^2$ x 10^3	$\alpha_2\sigma_{SMB}^2$ x 10^3	$\alpha_3\sigma_{HML}^2$ x 10^3	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10^3
Smallest Stocks	-0.018903 [-0.12094]	0.024288 [0.15539]	0.022268 [0.14247]	0.072918 [0.46652]
Small Stocks	-0.041103 [2.59282]	0.027370 [-1.72656]	0.023214 [-1.46436]	-0.010158 [0.64078]
Medium Stocks	-0.022793 [-0.63116]	0.006939 [0.19215]	0.024432 [0.67653]	0.004400 [0.12184]
Large Stocks	-0.018645 [0.27262]	0.010939 [-0.15994]	0.008226 [-0.12028]	-0.010701 [0.15647]
Largest Stocks	-0.022046 [-0.06513]	0.054295 [0.16041]	0.005820 [0.01719]	0.158373 [0.46790]
All Stocks	-0.030680 [-0.40314]	0.035443 [0.46572]	0.018499 [0.24307]	0.092815 [1.21959]

Notes to Table 6.7:

t-statistics appear in parentheses.
* indicates significance at the 5% level; ** indicates significance at the 10% level
Numbers in bracket are ratios of each component relative to the average contrarian profit. Profit contributions do not add up to a 100% due to estimation errors.

To summarize the results in this sub-section, when all stocks and closing prices are employed, UK stocks seem to react more strongly to the contemporaneous market and SMB factors, and to the lagged HML factor. The delayed reactions to the SMB and HML factors seem to contribute positively to contrarian profits in LSE while the delayed reactions to the market factor appear to contribute negatively to contrarian profits. However, overreaction to firm specific information seems to contribute most of the contrarian profits, while delayed reactions appear to have a smaller impact. These results hold for both constant and time-varying factor sensitivities. What is very important however is that the two additional FF factors explain a large portion of the results contributing more than 50% of the contrarian profits. Based on the last finding, it can be suggested that excluding these two factors could have biased the decomposition results. This will be further examined and quantified in section 6.5.4 where the results for the single factor model are presented.

6.5.2. Results using frequently trading stocks in the sample (closing prices)

Can the above findings be due to market frictions such as infrequent trading? Tables 6.8-6.10 report the same results as in sub-section 6.5.1, however, this time infrequent trading stocks are excluded from the sample (as described earlier in footnote 112), in order to examine whether infrequent trading has any effect on the sources of contrarian profits. More specifically, Table 6.8 reports the results from estimating equation (5.20) with the new sample. It is interesting to note that, when compared to the results in Table 6.5, the new results appear very similar. That is, returns react stronger to contemporaneous factor realizations (the reaction is also statistically significant) and react negatively to the HML contemporaneous factor realizations. Furthermore, the delayed reactions to the SMB and HML factors appear to contribute positively to contrarian profits, whilst reactions to the market factor appear to contribute negatively to contrarian profits in all cases, (indicating that the two cases where the contribution is positive in Table 6.5 might be due to infrequent trading). The decomposition of profits in Table 6.9 indicates a very similar pattern to the one observed before (as compared to results in Table 6.6), although each factor now contributes less on average.

Table 6.8
Average estimates of stock return sensitivities
(3 factors - Excluding Stocks that Trade Infrequently)

	$\bar{b}_{o,M}$	$\bar{b}_{1,M}$	$\hat{\delta}_M$
Smallest Stocks	0.71499	0.18112	0.019470
	(39.289)*	(12.028)*	
Small Stocks	0.59483	0.19466	0.005410
	(42.131)*	(16.524)*	
Medium Stocks	0.519739	0.21745	0.034093
	(44.825)*	(21.454)*	
Large Stocks	0.51266	0.19244	0.005151
	(45.878)*	(19.128)*	
Largest Stocks	0.62417	0.09750	0.006508
	(53.816)*	(10.728)*	
Average	**0.59328**	**0.17663**	**0.014126**
All Stocks	0.69257	0.21087	0.001809
	(47.435)*	(23.577)*	
	$\bar{b}_{o,SMB}$	$\bar{b}_{1,SMB}$	$\hat{\delta}_{SMB}$
Smallest Stocks	0.73247	0.03472	-0.442480
	(29.390)*	(1.543)	
Small Stocks	0.46953	0.02429	-0.199248
	(24.561)*	(1.431)	
Medium Stocks	0.29251	0.02780	-0.086220
	(18.893)*	(1.833)*	
Large Stocks	0.04481	-0.03328	-0.132895
	(2.933)*	(-2.476)*	
Largest Stocks	-0.24567	0.02229	-0.099521
	(-17.654)*	(1.680)**	
Average	**0.25873**	**0.015164**	**-0.192073**
All Stocks	0.10692	-0.01203	-0.024860
	(5.307)*	(-1.079)	
	$\bar{b}_{o,HML}$	$\bar{b}_{1,HML}$	$\hat{\delta}_{HML}$
Smallest Stocks	-0.19542	0.03713	-0.245868
	(-6.089)*	(1.333)	
Small Stocks	-0.23211	0.02626	-0.113819
	(-10.125)*	(1.273)	
Medium Stocks	-0.22789	0.01544	-0.16576
	(-11.648)*	(0.846)	
Large Stocks	-0.22591	0.00263	-0.134634
	(-11.995)*	(0.166)	
Largest Stocks	-0.18089	0.06009	-0.177955
	(-11.809)*	(4.188)*	
Average	**-0.21244**	**0.02831**	**-0.167607**
All Stocks	-0.13225	0.033371	-0.004598
	(-7.356)*	(2.847)*	

Notes to Table 6.8:

See Notes to Table 6.5

Table 6.9
Decomposition of contrarian profits
(3 factors - Excluding Stocks that Trade Infrequently)

	$-\hat{\delta}\sigma_M^2$ x10^3	$-\hat{\delta}\sigma_{SMB}^2$ x10^3	$-\hat{\delta}\sigma_{HML}^2$ x10^3
Smallest Stocks	-0.009191	0.094054	0.056941
Small Stocks	-0.002554	0.042352	0.026359
Medium Stocks	-0.016095	0.018327	0.038389
Large Stocks	-0.00243	0.028248	0.031180
Largest Stocks	-0.003072	0.021154	0.041213
All Stocks	-0.000854	0.005284	0.001065
	-Ω x10^3	$-\sigma_a^2$ x10^3	
Smallest Stocks	0.229988	-0.215994	
Small Stocks	0.086188	-0.147579	
Medium Stocks	0.045987	-0.122829	
Large Stocks	0.025111	-0.099133	
Largest Stocks	0.114961	-0.060084	
All Stocks	-0.014067	0.015580	

Notes to Table 6.9:

See Notes to Table 6.6

However, excluding infrequent trading stocks seems to affect the decomposition when allowing for time variation in factor sensitivities. As can be seen from Table 6.10 (Panel A) now only the coefficients on the SMB and HML factors are statistically significant for all cases (all sub-samples and the full sample). For example, the *t*-statistic on the coefficient of the SMB factor for the all-stock sample is 6.301 and the *t*-statistic on the coefficient of the HML factor is 7.697. Note that the coefficient γ (estimate of profits due to overreaction to firm-specific information) has a *t*-statistic of 1.397, i.e. it is statistically insignificant for the all-stock group. Overreaction to firm specific information seems to be significant only for the smallest sub-sample at the 5% and for the largest sub-sample at the 10%. Recall also (Table 6.4, Panel C) that contrarian strategies produced a positive profit with frequent trading stocks only for the two extreme sub-samples. These results taken together with the results in Table 6.10 (Panel B) indicate that with frequent trading stocks only the extreme size sub-samples produce profits and that the sources of these profits come in quite similar proportions from reactions to the SMB and HML factors and overreaction to firm-specific information. The large values observed in the Table for the all-stock group, are due to the fact that they are related to a profit that is almost zero both statistically (t-statistic: 0.197) and numerically ($\pi \times 10^3$: -0.001). As a result, the small magnitude of the profits drives the contributions to such high levels when employed in the ratio used to determine the contribution, and should not cause concern. Furthermore, the all-stock group for the frequently treading sample is represented by only 660 firms out of the almost 2000 firms originally in the data set, and should be approached cautiously (the same does not hold for the sub-samples as has been shown).

The findings in this sub-section seem to suggest that excluding infrequent trading stocks from the sample alters the decomposition results only for time-varying factor sensitivities. In this case, profits are related to delayed reactions to the SMB and HML factors, and to overreaction to the firm specific news component. This indicates that part of the contribution of the firm specific overreaction is related to infrequently trading stocks, and that it is important for researchers to account for this problem even in a well-developed market like the UK market.

Table 6.10
Decomposition of contrarian profits with time-varying factor sensitivities
(3 factors - Excluding Stocks that Trade Infrequently)

Panel A: Estimated coefficients

	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\alpha_2 \times 10^3$	$\alpha_3 \times 10^3$	$\gamma \times 10^3$
Smallest Stocks	-0.08704 (-1.558)	-31.76949 (-1.169)	321.96496 (3.938)*	135.73168 (4.544)*	31.89859 (2.086)*
Small Stocks	-0.06984 (-2.400)*	-63.96142 (-4.519)*	212.44737 (4.989)*	115.44263 (7.421)*	-3.15911 (-0.397)
Medium Stocks	-0.06270 (-2.111)*	-50.23478 (-3.478)*	131.40186 (3.024)*	79.18700 (4.988)*	-3.15243 (-0.388)
Large Stocks	-0.09724 (-5.356)*	-29.70145 (-3.364)*	66.40358 (2.500)*	35.14729 (3.622)*	7.90679 (1.591)
Largest Stocks	0.03768 (2.017)*	13.53981 (1.490)	74.14643 (2.712)*	88.15862 (8.826)*	8.46819 (1.656)**
All Stocks	-0.06122 (-3.773)*	-9.52502 (-1.194)	151.22545 (6.301)*	67.51784 (7.697)*	6.25909 (1.397)

Panel B: Contributions to contrarian Profits

	$\alpha_1\sigma_M^2 \times 10^3$	$\alpha_2\sigma_{SMB}^2 \times 10^3$	$\alpha_3\sigma_{HML}^2 \times 10^3$	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}) \times 10^3$
Smallest Stocks	-0.014997 [-0.18470]	0.074564 [0.91826]	0.028851 [0.35530]	0.078865 [0.97122]
Small Stocks	-0.030195 [0.89027]	0.049201 [-1.45065]	0.024538 [-0.72350]	-0.007810 [0.23028]
Medium Stocks	-0.023715 [0.50316]	0.030432 [-0.64567]	0.016832 [-0.35713]	-0.007794 [0.16537]
Large Stocks	-0.014021 [0.20420]	0.015378 [-0.22396]	0.007471 [-0.10880]	0.019548 [-0.28469]
Largest Stocks	0.006392 [0.063086]	0.017172 [0.16948]	0.018739 [0.18495]	0.020936 [0.206638]
All Stocks	-0.004497 [3.54317]	0.035023 [-27.59678]	0.014352 [-11.30867]	0.015475 [-12.193690]

Notes to Table 6.10:

See Notes to Table 6.7.

6.5.3. Results using all stocks in the sample (bid prices)

Kaul & Nimalendran (1990) question whether bid-ask errors or market overreaction are responsible for contrarian profits. They compare bid-ask returns and bid-to-bid returns to find the portion of results owed to overreaction only. Their findings indicate that the bid-ask error component explains over 50% (23%) of the small (large) firms' variance. Thus, the return reversals could be due to lead-lag relations and bid-ask errors. Kaul & Gultekin (1997) also contrast bid-ask returns to bid returns (using bid-to-bid returns to avoid bid-ask biases), and find that for NASDAQ all profits are due to the bid-ask bounce, whilst for AMEX and NYSE, on average half of the profits are due to bid-ask errors. There have been, however, studies that disagree with the above findings. For example, Loughran & Ritter (1996) use NYSE and AMEX data for the period 1928 to 1985, and find that it is risk and overreaction and not bid-ask biases that explain profits. Furthermore, JT find that the bid-ask bias is not a problem for the US market when they compare a sample based on closing prices with a bid-to-bid sample, and find no difference in contrarian profits. The evidence is conflicting, and it is thus important to determine whether the dataset employed in this chapter suffers from similar problems.

This section investigates the effect of bid-ask bias on results. That is, it follows JT and the other studies mentioned in the previous paragraph, and decomposes profits using bid-to-bid (the composition of this sample is discussed earlier in footnote 111) rather than closing prices. The results are presented in Tables 6.11-6.13, and indicate that using bid prices changes things only when allowing for time-variation in factor sensitivities. More specifically, the findings in Table 6.11 are very similar (albeit the slightly smaller betas) to the findings in Table 6.5: returns react stronger to contemporaneous factor realizations (the reaction is also statistically significant) and react negatively to the HML contemporaneous factor realizations. In addition, as was the case for the closing prices in Table 6.5, the reactions to the SMB and HML factors appear to contribute positively to contrarian profits, whilst reactions to the market factor appear to contribute negatively to contrarian profits. The decomposition of profits in Table 6.12 indicates a very similar pattern as before (that is, when compared to results in Table 6.6), although the contribution of each factor to profits is now slightly lower.

As the reader has probably noticed, as for the infrequent trading adjustment, the results for the bid-to-bid returns change mainly when considering time-varying factors. For example, as can be seen from Table 6.13 (Panel A) the coefficients on the SMB and HML factors appear statistically significant for most sub-samples, while the market factor is significant only for the large sub-sample with a t-statistic of 3.735. The t-statistic on the coefficient of the SMB factor for the largest stock sub-sample is 4.620 and the t-statistic on the coefficient of the HML factor is 11.059. Note that the coefficient γ is statistically significant for all sub-samplcs and the full sample. The above significance for SMB and HML, combined with the insignificance of the market factor, indicate that had the chapter not used a three-factor model and had it focused on the market factor as the only common factor, it would have probably lost a lot of significant information, but this important point is revisited in the next section. Panel B provides estimates of the contrarian profits due to reactions to the three common factors and overreaction to firm specific information. It can be seen that the contrarian profits due to firm-specific overreaction are significantly larger, when compared with the ones in Table 6.7, especially for the smaller sub-samples. The findings in this sub-section indicate that when using bid-to-bid rather than closing prices the results change only when time variation is allowed. In this case, profits come mainly from overreaction to the firm specific component of returns that contributes positively towards profits and more than it did earlier. The bid-ask bias does not provide a complete explanation for contrarian profits, and it does not reduce the contribution of the firm specific component. Furthermore, as was the case for Table 6.7, firm specific overreaction always contributes positively towards profits. In the case of the medium-sized stocks (Table 6.13, Panel B), the firm specific contribution is canceled out by the SMB and HML factors negative contribution, while for the large sub-sample some of the firm specific contribution is reduced. This is due to the SMB and HML factors negative contribution, and perhaps partly related to some other factors not included in the model.

Table 6.11
Average estimates of stock return sensitivities (3 factors - bid prices)

	$\bar{b}_{o,M}$	$\bar{b}_{1,M}$	$\hat{\delta}_M$
Smallest Stocks	0.56146	0.17786	0.06899
	(25.999)*	(9.214)*	
Small Stocks	0.43360	0.18709	0.02413
	(28.161)*	(13.384)*	
Medium Stocks	0.44890	0.17653	0.03727
	(32.272)*	(14.598)*	
Large Stocks	0.42106	0.15309	0.05193
	(32.536)*	(13.719)*	
Largest Stocks	0.53717	0.06328	-0.00422
	(40.160)*	(6.279)*	
Average	**0.48044**	**0.15157**	**0.03562**
All Stocks	0.53131	0.21904	0.011206
	(57.680)*	(32.562)*	
	$\bar{b}_{o,SMB}$	$\bar{b}_{1,SMB}$	$\hat{\delta}_{SMB}$
Smallest Stocks	0.57928	0.02202	-0.28507
	(20.425)*	(0.848)	
Small Stocks	0.30902	-0.00051	-0.16922
	(15.545)*	(-0.026)	
Medium Stocks	0.23284	-0.03813	-0.12323
	(13.561)*	(-2.283)*	
Large Stocks	-0.00851	-0.10720	-0.05745
	(-0.530)	(-6.985)*	
Largest Stocks	-0.27599	-0.06166	-0.09064
	(-18.607)*	(-4.831)*	
Average	**0.16733**	**-0.03710**	**-0.14512**
All Stocks	0.21212	0.00804	-0.01051
	(16.690)*	(0.924)	
	$\bar{b}_{o,HML}$	$\bar{b}_{1,HML}$	$\hat{\delta}_{HML}$
Smallest Stocks	-0.20999	0.11393	-0.26007
	(-5.940)*	(3.502)*	
Small Stocks	-0.19981	0.07843	-0.20122
	(-7.643)*	(3.260)*	
Medium Stocks	-0.20925	0.07511	-0.15368
	(-9.282)*	(3.807)*	
Large Stocks	-0.25390	0.04720	-0.02543
	(-12.774)*	(2.735)*	
Largest Stocks	-0.16958	0.08790	-0.16618
	(-9.447)*	(5.610)*	
Average	**-0.20851**	**0.08051**	**-0.16132**
All Stocks	-0.15326	0.04394	-0.00278
	(-12.329)	(5.709)	

Notes to Table 6.11:

See Notes to Table 6.5.

Table 6.12
Decomposition of contrarian profits (3 factors - bid prices)

	$-\hat{\delta\sigma}_{M}^{2}$ x10^3	$-\hat{\delta\sigma}_{SMB}^{2}$ x10^3	$-\hat{\delta\sigma}_{HML}^{2}$ x10^3
Smallest Stocks	-0.032568	0.066020	0.055281
Small Stocks	-0.011391	0.039190	0.042771
Medium Stocks	-0.017594	0.028539	0.032666
Large Stocks	-0.024515	0.013305	0.005405
Largest Stocks	0.001992	0.020991	0.035323
All Stocks	-0.005290	0.002434	0.000591
	$-\Omega$ x10^3	$-\sigma_{a}^{2}$ x10^3	
Smallest Stocks	0.264064	-0.194724	
Small Stocks	0.066139	-0.129557	
Medium Stocks	-0.009948	-0.115085	
Large Stocks	0.019544	-0.088714	
Largest Stocks	0.111820	-0.058128	
All Stocks	0.047847	-0.011494	

Notes to Table 6.12:

See Notes to Table 6.6.

Table 6.13
Decomposition of contrarian profits with time-varying factor sensitivities
(3 factors - bid prices)

Panel A: Estimated coefficients

	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\alpha_2 \times 10^3$	$\alpha_3 \times 10^3$	$\gamma \times 10^3$
Smallest Stocks	-0.32663 (-3.436)*	-15.77024 (-0.462)	-8.15782 (-0.078)	65.22539 (1.728)**	114.06395 (4.626)*
Small Stocks	-0.80117 (-3.869)*	-64.64017 (-0.869)	-435.05206 (-1.903)**	95.44440 (1.161)	299.59368 (5.577)*
Medium Stocks	-0.09860 (-3.459)*	7.45052 (0.727)	112.32887 (3.570)*	88.55877 (7.823)*	-13.56615 (-1.835)**
Large Stocks	-0.02731 (-1.099)	33.34247 (3.735)*	21.30174 (0.777)	26.69069 (2.705)*	-14.95185 (-2.320)*
Largest Stocks	-0.01631 (-0.608)	-12.20981 (-1.268)	136.67044 (4.620)*	117.67789 (11.059)*	17.06446 (2.455)*
All Stocks	-0.06429 (-1.279)	-18.83851 (-1.035)	48.69727 (0.870)	130.73763 (6.501)*	34.32832 (2.622)*

Panel B: Contributions to contrarian Profits

	$\alpha_1\sigma^2_M \times 10^3$	$\alpha_2\sigma^2_{SMB} \times 10^3$	$\alpha_3\sigma^2_{HML} \times 10^3$	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}) \times 10^3$
Smallest Stocks	-0.007445 [-0.12969]	-0.001889 [-0.03291]	0.013864 [0.24151]	0.368507 [6.41923]
Small Stocks	-0.030515 [-0.40909]	-0.100754 [-1.35071]	0.020288 [0.27198]	0.967899 [12.97566]
Medium Stocks	0.003517 [-0.03874]	0.026014 [-0.28656]	0.018824 [-0.20735]	-0.043828 [0.48278]
Large Stocks	0.015740 [-0.32593]	0.004933 [-0.10215]	0.005673 [-0.11748]	-0.048305 [1.00024]
Largest Stocks	-0.005764 [-0.06022]	0.031652 [0.33068]	0.025014 [0.26133]	0.055130 [0.57597]
All Stocks	-0.008893 [-0.30818]	0.011278 [0.39081]	0.027790 [0.96299]	0.110905 [3.84315]

Notes to Table 6.13:

See Notes to Table 6.7.

6.5.4. Results using a single-factor model

In their 1995 decomposition of US contrarian profits JT use a single (market) factor model. However, as the reader has probably noticed so far, the SMB and HML factors do contribute a lot of information for both the ASE and the UK, and not including these factors would have distorted the findings in the case of ASE as the previous chapter exhibited. This would happen because to the extent that the missing factors are not correlated with the market factor, most of the missing information affects the residuals and thus the firm specific component of returns (as defined it the current study by equation (5.10)).

It would be very interesting to quantify the magnitude of the possible bias, as has been done in the case of the ASE. Furthermore, it would also be interesting to be able to compare the UK findings in this paper with the US findings in the JT paper. To this end, the decomposition described in chapter V. relevant to the single factor model, is repeated for all return specifications and the results are presented in this sub-section. Tables 6.14 and 6.15 present the findings for all the stocks in the sample using closing prices, while Table 6.16 and Table 6.17 present the findings for a sample of frequently trading stocks. Finally, Table 6.18 and Table 6.19 present to the reader, the findings for all stocks using bid-to-bid rather than closing prices. These tables are provided in the Appendix of the chapter, given that the relevant question has already been analysed in the main body of the thesis for ASE, and they provide here just additional evidence for the particular sample. Tables 6.20 and 21 show evidence that there is no April effect, since results are similar with the full sample single factor results.

From Tables 6.14 & 6.15 it can be observed that when using a single-factor model for all stocks and closing prices, stock reactions are stronger for the contemporaneous period, but part of the reaction is incorporated in prices with a lag (as for the three-factor model). These (delayed) reactions appear to contribute to contrarian profits in the same way that they did for the three factor model results in Table 6.5 (positive δ). The estimates of contrarian profits due to the common factor realizations are small and negative, whilst the part of profits due to overreaction is much larger (especially for the smaller sub-samples). However, the results seem to indicate that there could be a negative contribution of the firm specific component to profits unlike the results in Table 6.6, and this is most probably related to the distortion caused by leaving out the two significant SMB and HML factors. Allowing for time-variation, 154.42% of the profits are due to firm-specific overreaction and approximately -28.14% are due to common factors. Notice that not including the two additional factors in the model would add about 32% of irrelevant structure to the firm-specific component (increasing its contribution to 1.544 from 1.220). Furthermore, the differences between the contributions of each factor vary significantly from sub-sample to sub-sample when using the single-factor model; using the three-factor model however, depresses these erratic movements as seen in Table 6.7, and there are not as many differences between sub-samples.

When closing prices for frequently trading stocks are used (see Tables 6.16 & 6.17), stock reactions to the common factors (which still contribute negatively to contrarian profits in most cases) are slightly stronger. The estimates of contrarian profits due to the common factor realizations are small and negative, whilst the part of profits due to overreaction is much larger (especially for smaller firms). Comparing these findings to the ones for the same sample but with the three-factor model in Tables 6.8 and 6.9, one can see that although the lagged betas are quite similar in value, and the average of the contemporaneous beta is not very different, there is a significant downward shift in the contemporaneous betas of the three smaller sub-samples. Furthermore, the firm specific reaction contribution is now lower for all sub-samples and the all-firms group, indicating that the lack of the two additional factors has (as speculated earlier) affected the residual of the single-factor variant of equation (5.10) and has thus added negative structure on the firm specific component.

This is a very important finding, and indicates that using a single-factor model where more factors are actually relevant can bias results for the UK market. Allowing for time-variation confirms this finding (at this stage recall that only the two extreme sub-samples make positive contrarian profits without infrequent trading stocks in the sample). For example, the contribution of firm specific overreaction to contrarian profits of the smallest firms appears to be 176% whilst the contribution of market reactions is around 2% (compared to 90% and -17% respectively for the three-factor model in Table 6.10). Similarly, the contribution of firm specific overreaction to contrarian profits of largest firms appears to be 46% whilst the contribution of market reactions is around 10% (from 20% and 6% respectively in Table 6.10). In this last case, it can be seen that excluding the SMB and HML factors excludes about 17% and 18.5% of information respectively (Table 6.10 Panel B), of which 4% and 26% is added to the common and firm specific factor respectively in Table 6.17 (where single factor results are presented).

Finally, for bid-to-bid single-factor results, in Table 6.18 although the reaction of the stocks to the lagged factor is similar to the one in Table 6.11 (multifactor bid-to-bid results), the contemporaneous betas are now depressed (increased) for larger (smaller) sub-samples. This shows the downward (upward) bias introduced again from the single factor model in the contemporaneous beta estimates. The contributions of the common factors are not very different from Table 6.12, but the firm specific component contribution is once again much lower. This is due to the negative effect of the SMB and HML factors (see negative sign in Table 6.11 for all HML and some SMB contemporaneous betas) that are now not included in the model.[115] Allowing for time-variation in factor sensitivities, confirms this finding. For example, the contribution of firm specific overreaction to contrarian profits of largest firms appears to be around 50% higher when three instead of one factor are considered, whilst the market factor contribution is 9% less.

Overall, for all return specifications the beta coefficients with the single-factor model follow similar patterns with the ones for the three-factor model, and suggest that UK stock returns react stronger to the contemporaneous market factor rather than the lagged factor. The market factor contributions are not very different than for the three-factor model. However, the firm specific contributions are smaller on average for the single-factor model, consistent with

[115] And thus affect the firm specific component that is related to the error of equation 16.

the fact that the two (missing) factors have negative slopes in most cases, and not having them in the model affects the firm specific component negatively. On average, results persist irrespective of market frictions such as bid-ask-bias and infrequent trading, and show that the single factor model would have biased the estimates of firm specific contribution, and the bias would range from about 24% for all stock up to 67% for frequently trading stocks. Jegadeesh and Titman (1995) also find (for US stocks) stronger reactions to the contemporaneous market factor and a part of the effect to be incorporated in prices with a lag. However, the magnitudes of the profits and the contributions vary as discussed earlier. Furthermore, JT find that (delayed) common factor reactions contribute positively to contrarian profits, thought the decomposition indicates that for the UK the resulting lead-lag effect contributes negatively in most cases to contrarian profits. As in JT, most of the contrarian profits are due to overreaction to firm-specific information. These results don't change even after allowing time-variation in factor sensitivities (by taking the demeaned factors to allow for the measurement of the different effect of factor changes on profits).

Put simply, the effect of using a single-factor model instead of a multifactor model is visible mainly on the firm-specific component, which in most cases is biased upwards if the SMB and HML factors are not included, and the magnitude of the bias is up to 67% for the dataset employed in this chapter.

6.6 Comparisons of LSE with the ASE

As it has been mentioned in several occasions in this thesis, theory and practice suggest that larger and more developed capital markets suffer less from information asymmetries than smaller ones do. This is because, more investors and sophisticated analysts follow listed firms in larger and more developed markets and help the market to adjust to information faster and more accurately (Hong et al., 2000). By comparing the contrarian profits of the well-developed LSE (Table 6.4) and the less-developed ASE (Table 5.3), this expectation can be put to the test, at least as far as the two markets analyzed in the current thesis are concerned. More specifically, if the above expectation is correct, contrarian profits should be more pronounced for the ASE than for the LSE.

Table 5.3 shows that profits are positive and statistically significant for the all-stock group, for all five size-sub-samples, and for all return specifications for the ASE (apart for the smallest firms in Panel A only). This does not hold for the LSE (Table 6.4), where in most cases the all-stock group does not exhibit statistically significant profits. As regards the sub-samples, in most cases only the extreme size portfolios exhibit profits, whilst for other sub-samples profits are most times either insignificant or significantly negative. The only situation where contrarian profits are significant for the LSE for all sub-samples is in Panel E (Table 6.4), for the three factor model adjusted returns. This is probably related to the fact that past winners are more risky than past losers, as chapter IV. has shown (consistent with DeBondt and Thaler 1985). Nevertheless, even in this single case it can be seen that the magnitude of the UK profits is still higher for the two extreme size sub-samples and much lower compared to ASE. For example, let us look in to the three-factor adjusted returns. Profits for the all-stock group are 0.40 for ASE (Table 5.3 Panel D) and 0.07 for the LSE (Table 6.4 Panel E). Looking into the smallest stocks the figures are 0.46 and 0.25 for ASE and LSE respectively, while for small, medium, large and largest stocks the figures are (ASE) 0.398 & (LSE) 0.09, (ASE) 0.46 & (LSE) 0.06, (ASE) 0.48 & (LSE) 0.03, and (ASE) 0.54 & (LSE) 0.12 respectively. It can therefore be suggested that the expectation discussed above is true: predictable profits are higher and more significant for less developed markets like the ASE than they are for more developed markets like the LSE. In addition, although microstructure biases have some explanatory power for both markets and could account for some profits, contrarian strategies are still profitable after controlling for them, albeit the profits are smaller.

The above finding, that the LSE is more "efficient" and less prone to filter rules, is coherent with the fact that stock returns for the LSE are more (less) strongly related to the contemporaneous (lagged) common factors than in the case of ASE. For example, comparing the two markets, on LSE (Table 6.5) the average contemporaneous estimated market slope coefficient is 0.555 while the lagged one is 0.173. For the ASE on the other hand (Table 5.5), the average contemporaneous beta is much smaller (0.395), while the average lagged beta is much larger (0.485). Looking into sub-samples, it can be observed that smallest stocks in the LSE have a contemporaneous estimated market slope coefficient equal to 0.646, and a lagged coefficient equal to 0.139. At the same time, the ASE (Table 5.5) has a contemporaneous beta equal to 0.387 and a lagged one equal to 0.367 for the same size sub-sample. One can clearly see in these tables, that the same holds on average for the remaining size sub-samples and for the other two factors as well.

According to the previous paragraph, LSE stocks are more strongly related to "common news" of the current period and less to the "common news" of the past; in other words the earlier assertion that prices adjust to information more quickly in well-developed markets akin to the LSE as opposed to less-developed ones like the ASE, is once more supported. This is also consistent with the fact that the common factors contribution to contrarian profits are much lower for LSE (Table 6.6), than they are for ASE (Table 5.6), since prices in the LSE seem to react to information faster than in the ASE, and any contribution of filter rules to profits is diminished. With respect to the contribution of firm specific news, comparing the same tables as above indicates that for ASE moving from smaller to largest sub-samples, the contribution of the firm specific component (given by $-\Omega$) increases, unless the sample is adjusted for thin trading using an AR(1) model (Table 5.9), in which case the slope coefficients also become similar in character to the ones for LSE (see Table 5.8). Results for the UK however, move in the opposite direction even before any adjustment, and are consistent with the US results of JT in the sense that firm specific news affect profits progressively less on average as one moves form smallest to largest firms. This shows that the higher profitability of the extreme size sub-samples in the LSE is not related to overreaction per se, but to some other factor or premium. This last suggestion is also supported by the fact that there are higher unexplained profits for LSE than for ASE (as given by $-\sigma_a^2$ in the same tables). It can therefore be suggested that the higher contrarian profitability of extreme size sub-samples is not a strange and unexpected result as it would initially seem to be, given that overreaction contribution of firm specific news behaves in an expected manner (becoming smaller for larger stocks) and is not the driving power of the results. Allowing for non-constant factor sensitivities does not provide any specific pattern, apart for when a sample of stocks adjusted for infrequent trading in LSE (Table 6.10) and infrequent-thin trading for ASE (Table 5.10) are considered; where it is observed that the firm specific overreaction has a higher contribution for all size sub-samples in ASE than in LSE[116]. The results also show that the two additional factors are relevant in both markets and offer a substantial amount of contribution as has already been stated, measured, and analytically discussed in this and the previous chapter and will not be repeated here.

Overall, it can be concluded that contrarian strategies are more profitable for the less-developed ASE than the well-developed LSE, even when considering microstructure biases. The ASE is more affected than the UK by microstructure biases, given that both their magnitude and their character changes once these biases are accounted, while in the UK only the magnitude of results is affected. However, statistically significant profits can be made in both markets; and the best strategy is (given that larger stocks exhibit high contrarian profits) to invest only in largest more liquid winners and losers in order to minimise risk, and lower the transaction, carrying, and monitoring costs.

[116] We do not refer to the all-stock group due to the reasons that we have mentioned earlier; that the very high contributions in LSE are due to very small and statistically insignificant profits.

6.7 Conclusion

This chapter employs weekly price observations for all stocks listed in the London Stock Exchange for the period between 1984 and 2000, in order to investigate the existence of short-term contrarian profits and the sources of these profits in the main UK capital market. Evidence of contrarian profits would imply return predictability and rejection of informational efficiency of asset prices in the weak form.

The first important question that the chapter attempts to address is the issue of predictability of UK stock returns, more specifically, whether UK portfolios constructed based on past returns can earn arbitrage profits. The main result that emerges from the empirical analysis indicates that this is the case, and that contrarian strategies are profitable for UK stocks. That is, zero-investment contrarian portfolios that short every week the previous week's winners, and go long on previous week's losers, produce significant profits. In fact, contrarian profits persist even after adjustments for market frictions, such as infrequent trading and bid-ask biases are made, and irrespective of whether raw or risk-adjusted returns are employed for the calculation of contrarian profits. In addition, profits appear statistically and economically significant and more pronounced for extreme market capitalization portfolios (smallest & highest). Therefore, investors could employ short-term contrarian strategies in the LSE for the smallest or largest firms in the market. It would be sensible however, to focus on the largest firms that are more liquid and less risky.

The second important question the chapter attempts to address is related to the sources of the above-discussed profits. More specifically, whether these profits are due to investor overreaction to firm specific information, as suggested in previous studies for the US market, or due to delayed reactions and lead-lag effects. The results indicate that UK stock prices do not fully react contemporaneously to the Fama and French (1995) factors, but part of the effect is incorporated in prices with a lag, and these delayed reactions of the two additional FF factors contribute to contrarian profits. However, further tests indicate that the magnitude of the contribution of the delayed reactions to contrarian profits is small, while the magnitude of the contribution of investor overreaction to firm specific information to profits is far larger. Furthermore, the contribution of overreaction to firm specific news grows as one moves from smaller stocks to larger ones. It is thus firm specific reaction that investors can cash in, and not common factor reaction (consistent with JT), which is small for SMB and HML, and negative for the Market consistent with Kang et al. (2002).

Another interesting finding is that even when the sample is adjusted for infrequent trading and bid-ask biases the main conclusion is the same (although magnitudes vary). However, when only frequently trading stocks are employed the magnitude of the contribution to profits of investor overreaction to firm specific information is reduced, while the magnitude of the contribution of delayed reactions to profits is increased. This suggests that part of the contribution of the overreaction effect may come from infrequently trading stocks, and thus consideration of this effect should be taken before concluding on the firm specific overreaction component contribution.

Comparing the results with the ones of the previous chapter for ASE, contrarian strategies are more pronounced in less developed markets than in well-developed ones; however, contrarian strategies can deliver profits in both sets of markets. This is consistent with the empirical evidence for both developing markets: Spain (Rodriguez & Fructuoso 2000), New Zealand (Bowman & Iverson 1998), Brazil (DaCosta & Newton 1994), Finland (Grinblatt & Keloharju 2000 etc), and well- developed markets like US, France, Germany (Brouwer, Van Der Put & Veld 1997, Richards 1997, etc) that have been already discussed in several occasions. Finally, in both markets and consistent with the JT study, in most cases the majority of profits are related to firm specific overreaction and not common factors, albeit the difference in favor of firm specific contribution is not as large as JT suggest, and sometimes it approaches the 50% level for each.

The implications of the above findings are multiple. With regards to financial theory, our results do not support market efficiency for either UK as was the case for Greece, since the future can be predicted based on the negative serial correlation of stock returns (i.e. based on past information). Furthermore, risk does not explain the results as efficient market advocates would suggest, and in fact, past losers are less risky than past winners (consistent with De Bondt and Thaler (1985) for the US, and Dissanaike (1997) for the UK), and thus, taking in to account for risk, increases contrarian profits. At the same time, infrequent trading and the bid ask bias do not explain contrarian profits (only a portion can be attributed to infrequent trading). This is further evidence inconsistent with market efficiency, given that it challenges the suggestion of efficient market supporters that microstructure biases explain results. Efficient market advocates have also suggested that results might be data specific for the US, but can be seen here they are not, given that the overreaction hypothesis is also present for the UK data employed in this chapter (and Greek data employed in the previous two chapters). There also seems to be a size-effect, not only for the smallest firms as would be expected but for the extreme sized firms, i.e. the smallest and largest; which is contrary to suggestions by Clare and Thomas (1995) that overreaction is related only to small firms.

In terms of literature, the findings are in general in line with the overreaction hypothesis, and to some extent they agree with JT. For example most of the profits (but not in every single case) come from firm specific news as JT suggest (contrary to Lo & Mackinley 1990), but these profits are much lower than JT argue because of the bias introduced when using the single factor model. In addition, the market factor contributes negatively towards contrarian profits some times, and not always positively as JT find. Furthermore, results in general are in line with other UK longer-term contrarian studies by Poterba and Summers (1988), Brouwer, Van Der Put & Veld (1997), Richards (1997), Dissanaike (1997), and Balvers, Wu, and Gilliland (1999). As regards the model used, findings suggest that the three factor model is superior (although not perfect itself) to the single-factor model, and one of the chapter's contributions to literature is that it quantifies the effect of using a single factor and finds that it mostly distorts the firm specific component contribution.

With respect to market participants, the chapter provides evidence that contrarian strategies in the LSE are not only profitable for longer-term strategies as previous studies have shown, but they are also profitable for shorter-term horizons. Furthermore, the profits are not due to taking on excess risk directly (as risk and three factor risk adjusted returns indicate), or indirectly (by investing in small less liquid stocks since profits exist for the largest stocks as well), or due to microstructure biases. With respect to regulators, results indirectly imply that any rule that decreases information asymmetries would work towards the reduction of overreaction, and substantially reduce return predictability related to it.

6.8 Appendix

Table 6.14
Average estimates of stock return sensitivities
(1 factor - all stocks - closing prices)

	$\bar{b}_0$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.33925	0.14286	0.05118
	(29.544)*	(13.626)*	
Small Stocks	0.3567	0.16157	0.03308
	(40.684)*	(21.513)*	
Medium Stocks	0.39253	0.20647	0.01210
	(47.649)	(29.205)*	
Large Stocks	0.48387	0.23161	0.03116
	(62.239)*	(37.835)*	
Largest Stocks	0.76018	0.11804	-0.00602
	(99.282)	(21.943)*	
Average	**0.46651**	**0.17211**	**0.0243**
All Stocks	0.50407	0.23532	0.00912
	(74.441)*	(57.382)*	
	$-\hat{\delta}\sigma_M^2$ x10^3	-Ω x10^3	$-\sigma_a^2$ x10^3
Smallest Stocks	-0.02416	0.19316	-0.21611
Small Stocks	-0.01562	0.06423	-0.17389
Medium Stocks	-0.00571	-0.01450	-0.12766
Large Stocks	-0.01471	-0.02727	-0.08749
Largest Stocks	0.00284	0.08653	-0.05477
All Stocks	-0.00431	-0.04587	-0.01272

Notes to Table 6.14:

The coefficients $\bar{b}_0$ and $\bar{b}_1$ are obtained from a simple version of equation (5.20), specifically by: $r_{it} = a_i + b_{0,i}r_{M,t} + b_{1,i}r_{M,t-1} + e_{i,t}$, which is estimated for the full sample, and for each year and each stock in each sub-sample separately. This provided estimates of α_i, b_0, b_1, for the full ample, and for each year and each sub-sample and the full sample as well. Then, $\bar{b}_0$ and $\bar{b}_1$ were calculated as the averages of b_0 and b_1 for each sub-sample and each stock for each year. An estimate of the potential contribution to contrarian profits of the differences in the timing of stock price reactions to the common factors is provided by $\hat{\delta}$, which was estimated as: $\hat{\delta} = \frac{1}{N}\sum_{i=1}^{N} E\{(b_{0,i} - \bar{b}_0)(b_{1,i} - \bar{b}_1)\}$. The term $-\hat{\delta}\sigma_M^2$ provides an estimate of the part of contrarian profits due to common factor reactions. The negative of the average autocovariance of the error term, Ω, defined as $\Omega \equiv \frac{1}{N}\sum_{i=1}^{N} \text{cov}(e_{i,t}, e_{i,t-1})$, provides an estimate of contrarian profits due to overreaction to firm-specific information. The negative of the cross-sectional variance of expected returns ($-\sigma_a^2$) provides an estimate of the profits that are not due to the previous two terms. t statistics in parentheses

Table 6.15
Decomposition of contrarian profits with time-varying factor sensitivities
(1 factor - all stocks - closing prices)

	α_0 x 10^3	α_1 x 10^3	γ x 10^3	$\alpha_1\sigma^2_M$ x 10^3	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10^3
Smallest Stocks	0.0916	-46.9385	20.4694	-0.0221587	0.08718589
	(1.431)	(-1.315)	(3.450)*	[-0.1417682]	[0.5578021]
Small Stocks	0.0142	-72.1049	1.0540	-0.0340393	0.00448933
	(0.603)	(-5.479)*	(0.481)	[2.1472557]	[-0.2831946]
Medium Stocks	-0.2610	-49.8252	74.8214	-0.0235215	0.3186889
	(-2.836)*	(-0.971)	(8.773)*	[-0.6513232]	[8.8246743]
Large Stocks	-0.0466	-34.8854	-1.177	-0.0164687	-0.0050132
	(-2.706)*	(-3.636)*	(-0.738)	[0.2407909]	[0.0732990]
Largest Stocks	0.1565	-26.3175	45.4736	-0.0124240	0.19368698
	(1.021)	(-0.308)	(3.201)*	[-0.0367055]	[0.5722306]
All Stocks	-0.0197	-45.3706	27.5902	-0.0214186	0.1175157
	(-0.551)	(-2.253)*	(8.242)*	[-0.2814]	[1.5442]

Notes to Table 6.15:

The coefficients α_0, α_1, and γ are obtained from the following decomposition of contrarian profits, π_t: $\pi_t = \alpha_0 + \alpha_1 (r_{M,t-1} - \bar{r}_M)^2 + \gamma\theta_{t-1} + u_t$, where $\theta_t = \frac{1}{N}\sum_{i=1}^{N} e^2_{i,t}$, $\bar{r}_M$ is the average common factor return, and $e_{i,t}$ are the residuals estimated from the equation in Table 6.14. The estimate of the contrarian profits due to delayed reactions to the common factor is given by the product of α_1 and the variance of the common factor ($\alpha_1\sigma^2_M$), while an estimate of contrarian profits due to overreaction is given by: $\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$. Numbers in bracket are ratios of each component relative to the average contrarian profit from Table 6.4, *t*-statistics appear in parentheses: * denotes significance at the 5%; ** denotes significance at the 10%. Profit contributions do not add up to a 100% due to estimation errors.

Table 6.16
Average estimates of stock return sensitivities
(1 factor - Excluding Stocks that Trade Infrequently - closing prices)

	$\bar{b}_0$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.45693 (37.321)*	0.18993 (18.739)*	0.03161
Small Stocks	0.45331 (47.230)*	0.20369 (24.807)*	0.01730
Medium Stocks	0.45098 (51.875)*	0.22177 (29.586)*	0.01812
Large Stocks	0.55565 (64.431)*	0.21634 (30.588)*	0.01031
Largest Stocks	0.77693 (90.521)*	0.08406 (14.863)*	-0.00870
Average	**0.53876**	**0.183158**	**0.01372**
All Stocks	0.68343 (59.477)*	0.22866 (30.531)*	-0.00274
	$-\hat{\delta}\sigma_M^2$ x10^3	$-\Omega$ x10^3	$-\sigma_a^2$ x10^3
Smallest Stocks	-0.01492	0.16219	-0.15707
Small Stocks	-0.00817	0.02930	-0.11287
Medium Stocks	-0.00856	-0.00144	-0.09101
Large Stocks	-0.00487	-0.02105	-0.07776
Largest Stocks	0.00411	0.10844	-0.03942
All Stocks	0.00129	-0.03466	-0.01010

Notes to Table 6.16:

See Notes to Table 6.14.

Table 6.17
Decomposition of contrarian profits with time-varying factor sensitivities (1 factor - Excluding Stocks that Trade Infrequently - closing prices)

	$\alpha_0 \times 10^3$	$\alpha_1 \times 10^3$	$\gamma \times 10^3$	$\alpha_1 \sigma_M^2 \times 10^3$	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}) \times 10^3$
Smallest Stocks					
	-0.07556	3.47468	60.19677	0.001640	0.153759
	(-1.346)	(0.132)	(4.138)*	[0.0187538]	[1.7579196]
Small Stocks					
	-0.05931	-39.87044	17.12576	-0.018822	0.043744
	(-1.971)*	(-2.833)*	(2.197)*	[0.5549528]	[-1.2897476]
Medium Stocks					
	-0.05377	-34.94105	9.06450	-0.016495	0.023153
	(-1.798)**	(-2.498)*	(1.170)	[0.3499747]	[-0.4912415]
Large Stocks					
	-0.09183	-21.99570	13.03128	-0.010384	0.033285
	(-5.073)*	(-2.598)*	(2.779)*	[0.1512219]	[-0.4847463]
Largest Stocks					
	0.04280	23.14706	18.39582	0.010927	0.046988
	(2.213)*	(2.560)*	(3.672)*	[0.1078497]	[0.4637592]
All Stocks					
	-0.05133	7.55276	18.23177	0.003566	0.046569
	(-3.034)*	(0.944)	(4.125)*	[-2.8095208]	[-36.6949001]

Notes to Table 6.17:

See Notes to Table 6.15.

Table 6.18
Average estimates of stock return sensitivities
(1 factor - all stocks - bid prices)

	$\bar{b}_o$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.36440	0.16429	0.08283
	(23.341)*	(12.612)*	
Small Stocks	0.36167	0.17975	-0.00284
	(30.470)*	(18.206)*	
Medium Stocks	0.40991	0.18181	0.04042
	(37.685)*	(22.439)*	
Large Stocks	0.49642	0.19381	0.032115
	(47.303)*	(24.847)*	
Largest Stocks	0.71893	0.07795	-0.00297
	(64.189)*	(11.113)*	
Average	**0.47027**	**0.15952**	**0.02991**
All Stocks	0.47293	0.20751	0.01087
	(55.709)*	(42.044)*	
	$-\hat{\delta}\sigma_M^2$ x10^3	-Ω x10^3	$-\sigma_a^2$ x10^3
Smallest Stocks	-0.03910	0.16167	-0.16147
Small Stocks	0.00134	0.00471	-0.11015
Medium Stocks	-0.01908	-0.06292	-0.09822
Large Stocks	-0.01516	-0.03578	-0.07391
Largest Stocks	0.00140	0.10067	-0.04598
All Stocks	-0.00513	0.02210	-0.01054

Notes to Table 6.18:

See Notes to Table 6.14.

Table 6.19
Decomposition of contrarian profits with time-varying factor sensitivities
(1 factor - all stocks - bid prices)

	α_0 x 10^3	α_1 x 10^3	γ x 10^3	$\alpha_1\sigma_M^2$ x 10^3	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10^3
Smallest Stocks					
	-0.33451	-15.03922	116.72895	-0.007010	0.388362
	(-3.620)*	(-0.463)	(5.345)*	[-0.1236740]	[6.7651032]
Small Stocks					
	-0.74588	-101.6280	254.5905	-0.047976	0.847034
	(-3.689)*	(-1.431)	(5.328)*	[-0.6431748]	[11.3553438]
Medium Stocks					
	-0.12815	19.13962	8.01148	0.009035	0.026655
	(-4.394)*	(1.869)**	(1.162)	[-0.0995281]	[-0.2936079]
Large Stocks					
	-0.03405	35.69625	-9.50868	0.016851	-0.031636
	(-1.401)	(4.182)*	(-1.655)	[-0.3489406]	[0.6550762]
Largest Stocks					
	-0.05040	2.47825	42.39335	0.0011699	0.141045
	(-1.777)**	(0.248)	(6.324)*	[0.0122229]	[1.4735615]
All Stocks					
	-0.11035	-13.27944	58.43454	-0.006269	0.194414
	(-2.207)*	(-0.751)	(4.925)*	[-0.2172363]	[6.7369782]

Notes to Table 6.19:

See Notes to Table 6.15.

Table 6.20
Average estimates of stock return sensitivities to current and lagged market returns and decomposition of contrarian profits (excluding April)

$$r_{it} = a_i + b_{0,i} r_{M,t} + b_{1,i} r_{M,t-1} + e_{i,t}$$

	$\bar{b}_0$	$\bar{b}_1$	$\hat{\delta}$
Smallest Stocks	0.320544	0.152331	0.023019
Small Stocks	0.347758	0.162236	0.035822
Medium Stocks	0.384989	0.206227	0.019737
Large Stocks	0.478020	0.229788	0.029109
Largest Stocks	0.762663	0.117035	-0.005691
Average	**0.4587948**	**0.1735234**	**0.0203992**
All Stocks	0.500336	0.242890	0.007596
	$-\hat{\delta}\sigma_M^2$ x10^3	-Ω x10^3	$-\sigma_a^2$ x10^3
Smallest Stocks	-0.010839	0.254352	-0.305332
Small Stocks	-0.016867	0.080291	-0.184109
Medium Stocks	-0.009293	-0.002338	-0.138381
Large Stocks	-0.013706	-0.012231	-0.103329
Largest Stocks	0.002680	0.088658	-0.059413
All Stocks	-0.003577	-0.044547	-0.0142319

Table 6.21
Decomposition of contrarian profits with time-varying factor sensitivities (excluding April)

$$\pi_t = \alpha_0 + \alpha_1 (r_{M,t-1} - \bar{r}_M)^2 + \gamma\theta_{t-1} + u_t$$

	α_0 x 10^3	α_1 x 10^3	γx 10^3	$\alpha_1\sigma_M^2$ x 10^3	$\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$ x 10^3
Smallest Stocks	0.11817	-54.3228	19.6019	-0.0255786	0.0849749
	(1.734)**	(-1.455)	(3.219)*		
Small Stocks	0.0139	-74.3569	0.19	-0.035012	0.0008234
	(0.572)	(-5.598)*	(0.088)		
Medium Stocks	-0.2559	-50.9582	74.3168	-0.0239944	0.3221661
	(-2.564)*	(-0.932)	(8.334)*		
Large Stocks	-0.0431	-36.8875	-1.5581	-0.017369	-0.0067546
	(-2.421)*	(-3.786)*	(-0.980)		
Largest Stocks	0.1733	-23.6782	44.9222	-0.011149	0.1947395
	(1.039)	(-0.259)	(3.014)*		
All Stocks	-0.0113	-47.3681	26.9887	-0.022304	0.1169970
	(-0.296)	(-2.236)*	(7.811)*	[-0.26845]	[1.4082]

Notes to Table 5:
t-statistics appear in parentheses.

CHAPTER VII.

CONCLUSION
&
THOUGHTS FOR FURTHER RESEARCH

One of the most controversial areas in finance during the last decades is on market behaviour and return predictability, and as chapter II. has shown, there are two main strands in the literature regarding this issue; one supporting return predictability and the other supporting that markets are efficient and unpredictable. Most of the early literature focuses on financial data, however, economic agents are human beings and as such they employ heuristics (preconceived ideas) that bias their decision-making. This seems to be the case for financial decision-making as well, since investors' intuitive judgement of probability is also biased (Kahneman et al. 1999), and they tend to overweight more resent information, and overreact to it to the extent that it is unexpected. Given that individuals make up financial markets, their behaviour is bound to have a collective effect on the overall behaviour of financial markets. Based on these findings, De Bondt and Thaler (1985) suggest the overreaction hypothesis, adding a behavioural aspect in financial research in the predictability and contrarian strategies area that is nowadays in the forefront of research.

The thesis, motivated by the above, aims to contribute to the discussion of financial market behaviour, more specifically, to verify whether stock returns are serially correlated and thus predictable, and whether this can lead to abnormal profits. Before reaching to any conclusions, the thesis investigates all the major possible explanations put forward by literature against abnormal profitability.

The thesis contributes to the literature in several ways. (1) It offers evidence on contrarian strategies for the ASE, for which, no earlier evidence exists. (2) It tests for the first time for short-term contrarian strategies for the UK market. Thus it tests for both a developing (Greek) and a well-developed market (UK), to offer insight to the differences of behaviour between such markets, and by doing so it offers further evidence as to whether the findings for the US -for which most of the studies have been carried out- are market specific, or hold for other markets as well. (3) The thesis takes into account for continuous changes in risk through time, unlike past studies that consider changes to occur once every one, two or three years. To do so, the thesis uses for the first time ever in the overreaction area the well known and used in other areas of finance Kalman filter. (4) The thesis brings together and controls for the first time in one study for all the main suggestions for return predictability in the literature, using several different ways in many cases. (5) It improves on the Jegadeesh and Titman (1995) methodology, by showing that the market factor can be unrelated to contrarian profits, and using it could bias downwards the common factor contribution to profits. (6) The present study proposes that the two additional Fama-French (1996) factors are more related to contrarian profits, and it shows that considering them, about half of the profits considered to be related to overreaction are actually related to these factors. In other words, Jegadeesh and Titman use factors that exaggerate the firm specific contribution and weaken common factor contribution.

More specifically, chapter IV, demonstrates that long-term (one to three years) contrarian strategies are profitable, and the profits are not due to risk or changes in risk between formation and testing periods. As a mater of fact, past losers who outperform past winners, are also less risky (consistent with De Bondt and

Thaler 1985). However, the definition of abnormal returns affects the findings (consistent with Chopra et al. 1992), and some of the profits -but not all- are related to continuous changes in risk (consistent with Ball and Kothari 1989). Seasonal effects do not explain findings, although profits can be lower in a particular month, namely August (consistent with Draper and Paudyal 1997), while the January effect does not explain results for this study (contrary to Zarowin 1990, and consistent with De Bondt and Thaler 1987). Furthermore, the chapter finds that there is an asymmetry in reversals, with losers exhibiting higher return reversals (consistent with most contrarian studies). The chapter also finds that the longer horizon three-year strategy delivers more profits than the one and two-year strategies consistent with De Bondt and Thaler (1985). As a mater of fact, the three-year strategy is always significantly profitable up to the second year, and profits in general fluctuate from 12% to 180%, throughout the holding period. These profits are not affected by transaction costs, because the strategy is not transaction-intensive and it performs a small number of transactions (twenty) just once every one, two, or three years. The results of this empirical chapter also show (consistent with the overreaction hypothesis) that the higher the formation period volatility is, the higher the future reversals and the contrarian profits are.

Based on the above long-term findings, it could be suggested that investors form their portfolios based on stock performance of the past two or three years and that they hold their portfolios for about two to three years. The higher the volatility in terms of standard deviation in the formation period, the higher profits in the holding period will be. Based on this, if volatility is very high in the past year, investors could also use a holding period of one year.

The second and third empirical chapters (chapters V. & VI. respectively), look into very short term contrarian strategies that rebalance portfolios weekly. More specifically, chapter V. looks into the Athens Stock Exchange of Greece and finds that statistically and economically significant contrarian profits exist. Consistent with Jegadeesh and Titman 1995, most of the profits are due to firm specific news and less to common news. However, the chapter shows that the three-factor model is more appropriate than the single factor model JT used, and using it, about half of the contribution allocated by the single-factor model to the firm specific component is actually due to the two additional FF factors. Furthermore, profits are not related to market frictions because the bid-ask bias is not present in the ASE (Milonas and Travlos, 2001), and profits are present even after infrequent and thin trading are both considered. However, although profits are not overall due to microstructure biases, thin trading does affect the individual performance of size-sorted portfolios, and their behaviour becomes consistent with the JT findings for the US only when the sample is treated for thin trading. Furthermore, profits are not related to risk irrespective of whether risk is considered as one-dimensional or multi-dimensional. Results validate earlier findings of chapter IV. according to which past losers are less risky than past winners, since by taking into account for risk the strategies become more profitable.

Chapter VI. performs short-term analysis for the well-developed and liquid UK market, and compares the results with the less-developed ASE. This is additionally interesting because the UK sample -unlike the ASE- can potentially suffer from the bid ask bias, because of the market-maker system used to enhance liquidity. Results indicate that contrarian strategies are both statistically and economically significant as in the ASE, albeit for the UK they are only significant for the two extreme size subsamples of the smallest and largest stocks. Smallest stocks movements however are also related to other factors not accounted for (that is factors other than firm specific news and the three-factors considered). With respect to market microstructure, it does not affect the character of the results but only the magnitudes (reducing profits, but not eliminating them). Also, the past losers for this sample are as for the ASE less risky than former winners.

The strategies in chapter V. and chapter VI. are very intensive, and if one takes into account for transaction costs, profits could vanish. For example, the UK chapter methodology buys or sells more than a thousand stocks weekly. Nonetheless, based on the findings (that provide evidence of profitability for larger firms) if investors focus only in larger more liquid and less risky stocks that deliver contrarian profits in both markets, they can reduce such costs. Furthermore, investors can avoid transacting on many stocks by performing their strategies for only the top and bottom 10% of stocks (ranked based on past performance), and not for all stocks. This would also reduce transaction costs and make the portfolios easier to manage and monitor, without having a significant effect in the profits. This is because, as it has been shown in all relevant studies without dispute, contrarian profits are higher for the most extreme performers, i.e. taking the top-bottom 10% delivers higher profits than taking the top or bottom 30%, 50% or 100% of past performers (see the literature review).

The Thesis concludes that contrarian strategies are profitable in both developing and developed markets, although profits are higher for developing markets, and are dispersed to stocks of all sizes for such markets. Profits can be made for both the very short run (weekly horizons) and the very long run (one year up to three years). Profits are not just compensation for increased risk, however they are lower in some cases if changes in risk are considered, and they are significant (at least for long-term strategies) even if transaction costs are taken into account, as discussed above. Furthermore, seasonality and market frictions do not explain contrarian success. All, the findings agree with the overreaction hypothesis predictions, and thus, market efficiency of even the weakest form is not supported, since the future can be predicted based on past information. This is more profound in the ASE developing market sample, given the larger information asymmetries, and the legal and other market-framework.

Findings indirectly suggest that if markets are to become more efficient, legal framework and the whole market structure especially in developing markets should be improved in such a way that will reduce information asymmetries and increase transparently. To this end, regulators could adopt rules that minimize false predictability, especially after very volatile time periods. One suggestions is that company accounting figures are released more often, and firms are called to publicly verify or deny rumours that cause confusion and overreaction, and properly quantify misjudged news that could or have distorted the intrinsic value of their stock (as this is considered to be by the existing models and theories). Heavy penalties could be enforced for those that are proven beyond any doubt to spread rumours that cause and sustain market anomalies. Firms will find that although in the short-run they might suffer loses in some cases from such policies, in the long run they will gain from the informational efficiency of the market, which will further reduce speculative attempts by market participants. They will also gain in the sense that the economy as a whole will allocate resources more efficiently to the best economic entities (firms) and not to the ones that gain due to anomalies. This will increase their capital and their investment opportunities.

As regards future research, the area of contrarian strategies is full of research potential with externalities for all areas of finance, be it corporate finance, spot or derivative markets etc. Thus part of the future research should focus on these areas. I am especially interested in trying to combine both overreaction and underreaction in one strategy. It is my opinion however, that the literature is still very close to where it was when De Bondt and Thaler stated the overreaction hypothesis in 1985. The same questions still demand answers on fundamental issues, such as measurement for risk and changes in risk, equilibrium models used etc. These questions need an answered before any real theoretical advances are taken. For example given that results are very sensitive to the model employed for the analysis, it might be a good idea start from repeating tests for the JT data using the three-factor model. This will enhance the generality of the conclusions drawn in this thesis. Furthermore measuring exact magnitude of the bias on the results for the single factor-model would also enhance the thesis claim that the three-factor model is superior. It would be even better if more general research were performed to test whether results are global and hold for all markets, or particular market features affect them; and for this issue, evidence is needed on different markets and microstructures, in order to determine the length to which findings could be affected by particular market characteristics. Furthermore, although the three-factor FF model provides a better description of stock returns than a single factor model, it does not capture all relevant information as shown. It is thus very interesting to suggest other multifactor models, where risk factors that proxy for risk, are not only stock market oriented, but capture macroeconomic risks as well, business cycles, interest rates, inflation etc. Another important area as mentioned above is the modelling of time variation in risk, and the need for use of different information diffusion processes each time in order to improve the capability of describing a pattern more realistically.

One must remember however, that whenever humans are involved, one cannot rely heavily on figures and formulas, but also needs to develop ideas branching from the work of Kahneman and Tversky (1999) in behavioural finance. This could be the suggestion of theoretical models that are based on availability, anchoring, overconfidence etc that would try to model at least a few aspects of average human behaviour and their effects in financial markets movements. This is the path leading to the future, and indeed the long route that the author intends to follow, building on the findings of the current thesis. Another way to rationalise the overreaction hypothesis, which is very mechanical, is by also using other more solid theoretical explanations and approaches. An example is regarding adaptive control processes as these were approached and explained earlier by Martel and Philippatos (1974), or thc cntropic detection of short-term Asset prices, as analysed earlier by Philippatos and Nawrocki (1973).

A promising area that is also related to behavioural finance, and needs to be researched, is momentum, especially given that it the only anomaly that FF (1996) model does not explain. Momentum is not inconsistent with return reversals and hence overreaction, since the evidence shows that the first occurs for medium-term strategies, while the second does for either very short or very long term. Representativness, anchoring, conservatism, overconfidence, and other heuristics and behavioural explanations can be combined to deliver a more realistic description of asset return behaviour, combining both momentum and return reversals.

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